Modelling the Distribution of Services for People with Learning Disabilities in Northern Ireland

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Executive summary

This report summarises the later phases of a project whose overall aims were:

- to collect information on the prevalence of learning disabilities (LD) in Northern Ireland;
- to establish the unit costs of providing services to people of different ages with different levels of severity of LD; and
- to develop resource allocation models from the costed prevalence data.

The type of modelling described in this report has been widely applied to resource allocation in health and social services, but as far as we know it has not previously been used to model the costs of services for LD. We suspect there are two main reasons for this. Firstly, the lack of reliable data on the prevalence of LD and the services provided to clients. Secondly, the belief that LD does not have any clear-cut socio-demographic correlates, with the possible exception of deprivation, and therefore it may be difficult to produce powerful or well-specified models. This project has to test whether suitable data can be obtained and whether credible resource allocation models can be developed for LD services.

Two earlier phases of the project carried out the groundwork for the modelling. The first estimated the prevalence of LD in Northern Ireland from client record systems and censuses, notably:

- data from SOSCARE and the Child Health System (Module V).
- social security data
- supplementary information (on people in hospital and residential care) from hospital in-patient records, Trusts and HSS Boards.

The numbers of persons identified in these sources and reported in the Prevalence

Study are listed in Table ES.1

Table ES.1: Count of persons with LD recorded on the main information systems used for the prevalence study

Location	**Trust Systems**		**Social Security**	
	N	**%**	**N**	**%**
Hospital*	390*	2.4%	192	2.6%
Residential+	1,703+	10.4%	825	11.1%
Community – Soscare only	*5,474*		-	-
Community – CHS only	*7,050^*		-	
Community – Both systems	*1,749*		-	-
Total Community	14,273~	87.2%	6422	86.3%
Total	**16,366~**	**100%**	**7439**	**100%**

** This number rises by 60 -80 if data from the Hospital in-patient survey is used along with data supplied by Boards (see later.) Thus between 440 and 470 persons are likely to be long-stay Hospital patients (see Section 4)*

+ Information on people in residential provision held on 'Trojan databases' gives a total figure of 1,884 persons. However this includes people being supported in ordinary housing and who may be counted in the community sub-population (see Section 5).

^ 6,531 persons were recorded only on CHS but this rises to 7,050 when 519 cases are added to compensate for the missing CHS data in UCHT (see Section 6).

The Prevalence Study was mainly concerned to establish the numbers of people with LD by Trust and Board and provide some supplementary information on their age sex and the severity of the disabilities. For the modelling in the later phases of the project we require the following minimum data requirement for each person with LD: their sex, age and ward of residence (or the originating ward for persons in care). If the modelling is to address the costs or volume of services, rather than just the numbers of clients, we also require some measure of the services provided to each individual, or, as a proxy, a measure of the severity of their LD.

SOSCARE and the Child Health System (CHS) were able to provide these information for clients in the community (N~14,000) and for some of the clients in residential care, sheltered accommodation and hospital. In the prevalence study, other data sources were used to supplement SOSCARE, especially for clients in hospital (N~400) and residential care (N~1,800). However, these additional sources do not always hold the full range of information provided for the modelling. The footnotes to Table ES.1 give some insight into the methods and difficulties of trying to combine estimates from different datasets.

For the present purposes, the most severe and unresolved data problem concerns the originating address for people in residential and hospital care. If we use the current (i.e. the care) address for these people, it will bias the modelling as the aim is to relate the socio-economic characteristics of relatively small areas (usually electoral wards) to the local prevalence of LD. Where a ward includes residential or hospital care for people with LD, we need to associate these people with the wards where they lived prior to being in care. However, it proved very difficult to obtain such details from current data systems, to the point where we felt unable to use originating address information for any LD clients in hospital or residential care.

There were two options: to exclude these groups, or to try to factor them into the community care dataset. The latter was attempted as we had sufficient detail on a large subset of the hospital and residential care groups to be able to weight up the (community based) numbers of clients per ward (controlling for age, sex and severity) to achieve the correct total for all clients in each Trust. The resulting weighted-up data set will have the same ward distribution as the SOSCARE data on clients in the community, but it is not unreasonable to assume that those in different types of care are likely to come from the same areas as the majority of people with LD who are cared for in the community.

Although the numbers in hospital and residential care are less than 20% of the total with LD it is important to test the effect of including these groups in the modelling, even if there is insufficient information to include them fully, not least because they tend to have different characteristics from those being cared for in the community. A comparison of the age/sex/severity composition of the three groups (Tables ES2a-c) shows that those in residential care and hospital tend to be older (more than 40% aged 50 and over, compared with 9.1% of those being cared for in the community). They also have more severe disabilities. Just over one quarter (25.6%) of those receiving care in the community have severe or profound disabilities compared with 37.9% of those in residential care and 66.7% of those in hospital care.

Table ES2a Age and Severity breakdown of clients in community (N=12197)

Age	Moderate	Severe/ Profound	Total
0-19	78.6%	21.4%	56.2%
20-34	70.5%	29.5%	22.3%
35-49	65.4%	34.6%	12.4%
50+	70.7%	29.3%	9.1%
Total	74.4%	25.6%	100.0%

Table ES2b Age and Severity breakdown of those in residential care (N=1671)

Age	Moderate	Severe/ Profound	Total
0-19	1.7%	1.0%	2.8%
20-34	10.1%	6.1%	16.3%
35-49	20.7%	12.6%	33.3%
50+	29.5%	18.1%	47.6%
Total	62.1%	37.9%	100.0%

Table ES2c Age and Severity breakdown of long-stay in-patients (N=415)

Age	Moderate	Severe/ Profound	Total
0-19	0.0%	0.8%	0.8%
20-34	5.8%	12.4%	18.2%
35-49	13.9%	25.4%	39.3%
50+	13.6%	28.1%	41.7%
Total	33.3%	66.7%	100.0%

The number of clients with LD per ward is the most important proxy for need to be used in the modelling. It has high variability and, as such, should distinguish those areas with high and low need. The method could be refined slightly if we are able to take some account of the different needs of individuals, perhaps through the volume or cost of the services they consume – though it also needs to be recognised that this may also obscure patterns of need if service cost does not reliably reflect need, not least where there are local variations in the use of services of different costs by people with similar needs.

Ideally, information on the services to individual clients and the costs of those services should be obtained from client record systems. As these details were not generally available, the project had to adopt an indirect approach. This took the form of a consensus building workshop that invited social and health care professionals to estimate the relative volume or cost of different types of services required by people with LD of different severity. The summary results from this exercise are shown in Table ES.3

Table ES.3 Service cost (volume) associated with different age and severity groups (from Prevalence Study)

Age	**Level of severity**	
	Mild/moderate	**Severe/Profound**
0-19	1.0	1.8
20-34	2.4	4.6
35-49	3.2	5.8
50+	3.2	4.9

These estimates were intended to be combined with measures of severity taken from SOSCARE, with some subsequent refinement by the researchers, so that cost weights could be attached to clients of different age and severity. It is important to note that the final weightings from the workshop do not provide costs for people receiving particular types of care, as for example in the Family and Child Care modelling, where there are unit costs for residential care, fostering etc. For LD clients, the weights are the average service costs for clients of a given age and severity, regardless of the type of care they receive. When these costs are multiplied by the numbers in each age and severity group they amount to the total cost of LD services in NI, but they do not reflect local differences in costs if say, a Trust decides to use very high or low cost options for particular groups. In many respects this is a more appropriate form of weighting than using actual local costs, as it is more likely to be a valid proxy for need.

Subsequent data translations

The data from the prevalence study and costing workshop were further cleaned and transformed prior to the modelling. The main stages were:

- Data cleaning, such as improving postcoding and data formats and identifying cases that had sufficient details to be included directly
- Weighting-up to take account of cases that could not be included directly
- Applying cost weights
- Computing the numbers of clients and costs per electoral ward
- Merging small wards into synthetic wards where either the activity or needs driver data are likely to contain too few cases to be reliable
- Standardising the ward level activity and cost data by age and sex – this was necessary because the prevalence study indicated wide variations in rates of people with LD by age and sex. An indirect form of standardisation was used (due to small client numbers) resulting in ratios of the actual to expected numbers of clients (and costs) per ward.

These manipulations of the basic client data resulted in four different standardised dependent variables based on:

- numbers of clients in the community
- clients in the community weighted by the cost of care for people in their age and severity group
- clients in the community weighted up by age and sex (at Trust level) to take account of the clients in residential and hospital care
- clients in the community weighted up by age and sex <u>and severity</u> to take account of the clients in residential and hospital care.

Additional dependent variables were computed for some of the sensitivity tests.

Choice of Needs drivers

A great deal of effort went into the construction of the dataset of potential needs drivers for the modelling – parts of which have also been used for the Physical and Sensory Disability and Family and Child Care analyses. The full dataset contains 81 variables of which the majority are derived from small area data from the 2001 Census, though there are also a number of indicators based on claimant counts and other administrative sources. The potential drivers for the LD modelling fall into four main groups:

General deprivation and social structure

The literature on the distribution of learning disabilities posits a relationship with deprivation, though there is not a substantial body of evidence to support this link. Nevertheless, we include a variety of both Census and administrative data based measures of deprivation as a priority. The variables chosen included measures of (and proxies for) low income as well as indicators of housing conditions. We also included several measures of social structure, such as one-parent households that are often associated with material deprivation.

Illness and general morbidity

The morbidity variables are mostly standardised versions of the replies to the two health questions in the Census. Standardised Mortality Ratios (SMRs) are also included in the dataset.

Child deprivation and circumstances of families with children

A selection of these variables was included because of the high proportion of young people receiving services for learning disabilities.

Educational attainment of the population

The 2001 Census recorded that approximately 42% of the population of Northern Ireland aged 16-64 had no educational qualifications. While many of the 0.9% of the population receiving services for learning disabilities may never acquire educational qualifications it does not necessarily follow that areas with lowest educational attainment will also include the highest rates of people with learning disabilities. Nevertheless, rates of people without educational qualifications and several other variables relating to education were included.

Supply variables

As for many health and social services, there is a possibility that the supply of, and access to, services for people with learning disabilities may influence the volume of services used. Ward level measures of access to services are not always easy to obtain or compute, but in this case we were provided with data on two types of relevant services: average travel times from each electoral ward to hospitals with specialised units for learning disabilities and to residential care homes with relevant places.

Modelling methodology

The overall approach to the modelling has been to start with a large number of potential needs drivers and progressively eliminate the less powerful or unstable predictors by a combination of statistical and theoretical criteria. The main steps are as follows:

- All possible variables were included in the regression model.
- Variables with both counter-intuitive signs and standard errors greater than their respective coefficients were eliminated. In the initial stages, due to the large number of variables, two or three variables were deleted at each re-estimation of the model.
- Variables with counter-intuitive signs irrespective of their significance level were rejected.
- Variables with intuitively correct signs were rejected on the basis of lack of statistical significance (selection criteria: $p>0.05$). At each re-estimation of the model any variables resulting in counter-intuitive signs were eliminated prior to searching for non-significant variables.
- Where the model appeared to be too narrowly based, attempts were made to

"force" variables relating to other types of phenomenon into the equation

- Modelling was repeated with and without the inclusion of the two supply side variables.
- The supply side variables were tested for endogeneity with the need drivers in the final models.
- Variables relating to phenomenon not covered by variables already in the model were forced into the model when there was evidence of poor specification.
- Other strategies used to improve specification included: changing the functional form and testing the influence of outliers.

Results

Four sets of modelling were conducted with dependent variables based on the four combinations shown in the table:

	Not weighted by cost	Weighted by cost
Community clients only	x	x
Community, residential and hospital clients (HRC)	x	x

Three classes of variables are used in the modelling

- Trust dummies;
- variables measuring access to LD related services (supply variables); and
- needs drivers.

Trust dummies

The purpose of including dummy variables for the Trusts is to eliminate systematic differences in the levels or costs of activity between Trusts – differences that might be caused by variations in local policy or historical differences in behaviour that we would not want to bias a national model.

Because identification and support of people with LD can vary considerably between areas, we expected the Trust dummies to have a considerable explanatory role. This proved to be the case. The proportion of overall variation explained by the dummies ranged from just under 10% for the weighted dependent based on the combined (HRC) data to 24% for the weighted dependent based on clients in the community. The high value in this last case will almost certainly be due to differences between Trusts in the criteria used to assign levels of severity being amplified by the severity based cost weightings.

Supply variables – the two variables available were not significant predictors of reduced levels of other services.

Needs drivers

One variable stood out in the modelling: the Census measure of educational non-attainment. This is consistently one of the strongest predictors of all the dependent variables in these models and is easy to justify intuitively. However because we suspected it may be acting as a proxy for more general forms of deprivation we decided to test the effects of removing it and forcing general measures of deprivation or income deprivation into the model. The high intercorrelation between these variables tended to make them relatively unstable in the models, For example, substituting the Noble income score for the measure of no-qualifications NOQUAL results in statistically insignificant values for the income score coefficient. When one of the other income related variables (Children in job seekers allowance households (KJAS)) is removed the Noble income score is still not significant. This income score continues to be insignificant when it is included with only one other variable, the proportion of adults with limiting long-tem illness. Much the same happens when measures of general deprivation were either included alongside NOQUAL or substituted for NOQUAL. Ward level correlations of NOQUAL and various deprivation and income measures with rates of learning disability clients within Trusts also point to NOQUAL as the most robust predictor of this set of variables.

The NOCARER variable occurs in most attempts to model the weighted combined dependent – as it does for the unweighted combined variable. Arguably it appears in the combined model because a major reason for older people with LD going into care is the lack of available carers in the family – or the inability of older parents to cope.

We have some concerns at the inclusion of the NOCENTH (households with no central heating) variable in the model as it does not appear to have a direct theoretical relevance to learning disabilities, although it may be a good proxy for aspects of socio-economic conditions not covered by the two other variables.

Given the strong correlations between the various needs drivers, it is very likely that other combinations of variables could perform as well as the models we are suggesting. However when we have substituted alternative variables covering similar topics and forced in variables when the range of drivers appears too limited, the suggested models proved surprisingly resilient to these tactics. In particular, the NOQUAL variable emerges strongly in almost all the modelling.

The recommended model for each of the dependent variables is shown in Table ES4. The variables and (unstandardised) coefficients are shown. They are estimated without the supply side factors as in all cases the coefficients of supply side variables were not significant and the variables were not endogenous.

All these models are well-specified. This has mainly been achieved by adopting a LOG-LIN form (the dependent variable is logged and the needs drivers are unlogged), but for the cost weighted models it has also been necessary to exclude a couple of outlying wards with very low values of activity.

Table ES4 Recommended models

Variable name	**Variable**	**Coefficient**
Model for unweighted dependent based on clients in community R-squared (Trust dummies 16.8, full model 50.7)		
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.675
KJAS	proportion of children in job seekers allowance households	1.653
LLTI	proportion of adults with limiting long-term illness	0.180
CONSTANT		-0.484

Model for weighted dependent based on clients in community R-squared (Trust dummies 24.4, full model 50.8)		
NOCENTH	proportion of households with no central heating	0.820
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.959
KDLA	proportion of children in disability living allowance households	3.231
CONSTANT		-0.694
Model for unweighted dependent based on combined dataset R-squared (Trust dummies 17.1, full model 50.4)		
NOCARER	proportion of persons in no carer households (including at least one person with LLTI)	0.579
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.567
KJAS	proportion of children in job seekers allowance households	1.769
KDLA	proportion of children in disability living allowance households	2.781
CONSTANT		-0.521
Model for weighted dependent based on combined dataset R-squared (Trust dummies 12.5, full model 42.5)		
NOCARER	proportion of persons in no carer households (including at least one person with LLTI)	0.745
NOCENTH	proportion of households with no central heating	0.914
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.587
KJAS	proportion of children in job seekers allowance households	1.452
KDLA	proportion of children in disability living allowance households	2.671
CONSTANT		-0.649

All but one of the models have respectable explanatory power (approximately 50%), the other has a value in excess of 40% and all are well specified. They have passed the sensitivity test of excluding one Board at a time and subdividing Belfast into four districts by increasing the number of dummy variables.

Unmet need corrections

We have attempted to add health variables and the Noble overall deprivation score into the models, following the Deloitte and Touche shortfall method for correcting for unmet need. None of the suggested variables was significant. In fact, we had already included the Noble score and limiting long-term illness in our standard dataset and only one of these, the LLTI, qualified as a variable in one of the models.

Final choice of model

The four recommended models differ in two respects: whether they are based on the combined numbers of hospital, residential and community clients, rather than just those in the community and whether a service cost is attached to each client (based on their age and severity of LD).

In principle it seems desirable to use a model that is based on all clients and is cost weighted – provided that these costs are a valid proxy for need.

The two models which are exclusively based on the clients in community care are open to the obvious objection that they ignore services (and clients) that account for a large minority, or even majority, of the expenditure in this PoC. Moreover, they ignore the fact that the clients in residential care and hospitals have different age and, to a lesser extent, severity profiles than those in the community.

The case for the models based on the community dataset is that they distribute monies in ways that are very similar to those that try to include clients in residential and hospital care and they do not rely on the weighting assumptions that are involved in constructing a combined dataset.

Arguments can also be made both for and against using the age-severity cost weights developed in the consensus building workshop. On the one hand, they are our only means of taking some account of severity, given the lack of data on the services actually used by individual clients. On the other hand, it is easy to object to the method of construction of the weights, or dispute the recommended values.

In practice, as can be seen from Table ES.5 the results from all these models are very similar when expressed as a percentage of the overall allocation they recommend for each Trust. The modelling does not appear to be sensitive to whether or not the combined or community dataset is used or whether client numbers or costs are modelled. The results of further tests (see Table 46 of the main report) endorse this point and show there is next to no measurable effect when the clients in hospital are excluded or when changes are made to the weighting to try to include clients from the prevalence study for whom there were no sub-Board details.

In many respects this lack of sensitivity is unsurprising. Owing to the limitations of the data on hospital and residential clients, these clients have had to be added at Trust level, and the Trust dummies will be bound to absorb some of the effect, especially in the modelling that is not cost weighted.

The similarity between the allocations from the cost weighted and unweighted models also shows very little sensitivity to the values of the weights. In effect, moving from no weights (i.e. all weights =1) to the weights from the workshop, only has an impact of more than 1% on the allocations for two Trusts and for no Trust exceeds 1.2%.

Table ES.5 Shares of overall PoC budget allocated to Trusts by recommended models

	Community only		Community, hosp and residential	
	Unweighted	Weighted	Unweighted	Weighted
(Model number)	1	2	3	4
S&E Belfast	9.0%	9.5%	8.7%	9.6%
N&W Belfast	11.7%	11.5%	12.3%	11.8%
Down&Lisburn	9.2%	9.5%	9.5%	9.1%
NDown&Ards	6.8%	6.8%	6.3%	6.8%
Causeway	5.6%	5.7%	5.4%	5.7%
Homefirst	17.9%	18.7%	17.3%	17.9%
Armagh&Dungannon	6.4%	6.4%	6.4%	6.4%
Newry&Mourne	6.1%	5.7%	6.3%	6.0%
Craigavon&Banbridge	7.4%	7.4%	7.4%	7.3%
Foyle	11.9%	10.7%	12.1%	11.0%
Sperrin Lakeland	8.1%	8.1%	8.3%	8.5%

Given the similarity of the results and the similar statistical properties of the four possible models, we feel there are no very strong grounds for choosing between them.

We do think there is a good prima facie case for using the combined (hospital, residential and community) dataset, however limited the method of weighting, because the residential and hospital clients tend to have different characteristics from those being cared for in the community.

The effect of adding these groups will only be fully realised if the age and severity related cost weights are also applied. This makes the case for the weighted combined model – though this has the lowest explanatory power.

In sum, if the weightings are a major concern then we would recommend the unweighted model based on the combined dataset, but on balance we just think the case for the combined weighted model is strongest – though this is a close call.

MAIN REPORT ON THE MODELLING

1. Introduction

This report describes some of the key features of modelling the need for services for people with learning disabilities in Northern Ireland. It builds on the results of two earlier phases of the study: one using Trust and hospital record systems to investigate the prevalence of learning disabilities; the other using a consensus building workshop to estimate the relative costs of services for people of different ages with different levels of disability.

Much of this report concentrates on the process of modelling levels of service activity against the socio-economic characteristics of the areas from which the recipients of the services originate. It also describes the various data translations that are needed before this modelling can take place.

2 Data Sources on Service Activity

The sources of the data on both the numbers of clients receiving services for learning disabilities and the services received have been documented in an earlier phase of the study, on the prevalence of learning disabilities in Northern Ireland.

The main sources were as follows:

- data from SOSCARE and the Child Health System (Module V);
- social security data; and
- supplementary information (on people in hospital and residential care) from hospital in-patient records, Trusts and HSS Boards.

The total numbers of clients identified in these sources and reported in the prevalence study are listed in Table 1. Because of the disparate sources used to compile these figures and the different levels of information available on each system, it may not be possible to include all these cases directly in the modelling.

Table 1: Count of persons with LD recorded on the main information systems used for the prevalence study

Location	Trust Systems		Social Security	
	N	%	N	%
Hospital*	390*	2.4%	192	2.6%
Residential+	1,703+	10.4%	825	11.1%
Community – Soscare only	*5,474*		-	-
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Total Community	14,273~	87.2%	6422	86.3%
Total	**16,366~**	**100%**	**7439**	**100%**

** This number rises by 60 -80 if data from the Hospital in-patient survey is used along with data supplied by Boards (see later.) Thus between 440 and 470 persons are likely to be long-stay Hospital patients (see Section 4)*

+ Information on people in residential provision held on 'Trojan databases' gives a total figure of 1,884 persons. However this includes people being supported in ordinary housing and who may be counted in the community sub-population (see Section 5).

^ 6,531 persons were recorded only on CHS but this rises to 7,050 when 519 cases are added to compensate for the missing CHS data in UCHT (see Section 6).

2.1 Data on Residential Clients

The details of clients in residential care were obtained from several sources and the numbers by Trust are shown in Table 2.

There are major differences between Trusts in the numbers of persons receiving residential care for learning disabilities. Expressed as a rate per 10,000 persons in the community, the numbers on SOSCARE vary from 7 in Foyle to 17.5 in Newry and Mourne and from 6.8 in Craigavon and Banbridge to 13.24 in North and West Belfast in the Trojan/Board estimates data.

Possible reasons for these variations are considered later in this paper: notably whether the proximity of residential establishments reduces the proportion of people with severe learning disabilities who receive care in the community. Such questions aside, clients in residential care can only be included in the small area modelling if we have details of their pre-care addresses. Finding such addresses can be doubly difficult since (1) prior address details are not always kept on health and social services computer systems and may need to be retrieved from manual records and (2) it may be impossible to find originating addresses for people who have moved between residential institutions or who have been in institutions for many years. After inspecting the addresses on the residential care dataset we concluded that a large majority are definitely institutional and most of the remainder refer to care homes or other institutions. Therefore almost all of these clients cannot be included in the modelling. Strategies for addressing this problem are discussed in a later section "combining the datasets".

Table 2: The numbers and percentage of people in residential accommodation recorded on Soscare, Social Security and Trojan Systems
(Table 10 from Prevalence Report)

Trust	**Soscare Records**	**Rate per 10,000**	**Social Sec ***	**Rate per 10,000**	**Trojan + Board updates**	**Rate per 10,000**
A&D	81^	7.94	93	9.12	132	12.94
C&B	120	9.83	29	2.38	83	6.80
N&M	152	17.46	82	9.43	113	12.99
SHSSB	**353**	**11.34**	**204**	**6.56**	**328~**	**10.54**
Foyle	113	6.97	44	2.72	134	8.27
Sperrin Lakeland	140	11.74	60	5.03	149	12.52
WHSSB	**253**	**9.00**	**104**	**3.70**	**283**	**10.07**
Homefirst	241	7.35	163	4.97	346	10.55
Causeway	141	12.25	50	4.35	104	10.51
NHSSB	**382**	**8.62**	**213**	**4.81**	**450**	**10.54**
Down Lisburn	129	7.47	71	4.11	206	11.94
NW Belfast	135	9.40	46	3.22	190	13.24
SE Belfast	267	13.32	40	2.00	248	12.38
UCHT	184	12.30	98	6.55	179	11.97
EHSSB	**715**	**10.73**	**255**	**3.82**	**823**	**12.36**
Total NI	**1703**	**10.10**	***825***	***4.90***	***1884****	***11.18****

^ The Trust's Procare system records 132 people in residential accommodation; the same figure as per Trojan listing.
** This total includes 359 persons reported to be in supported accommodation (258 EHSSB: 82 NHSSB: 7 SHSSB: 12 WHSSB). It is possible that some of these individuals are also counted in the community sub-population.*

There is a further question of whether to use the SOSCARE or Trojan derived figures. The former system includes a measure of severity (opening-up the possibility of using cost weights). The latter, in fact, only provides 1441 records with details of age sex and Trust, the figure of 1884 is derived with some up-weighting and apportionment. Moreover, as seen in the note to Table 2, the Trojan data may involve double counting with the SOSCARE records on clients in the community. For these reasons it is not practical to model the Trojan based figures. However, the sensitivity tests include a remodelling with the Trust totals weighted to the Trojan figures.

2.2 Data on hospital patients

Long stay hospital patients are described in the report on the prevalence study as follows:

> These are likely to be people who have no other address and who have been resident in hospital for some time. Most are awaiting resettlement in line with current policy, but a proportion of long-stay patients are likely to be receiving on-going treatment. This group does not include people who are admitted for short-term assessment and treatment and who have an address to which they can be discharged.

The prevalence study identified 390 clients in long-stay hospital settings from Trust record systems and 467 from the long-stay in-patient hospital census. The latter data cannot be used in the modelling because of lack of detail on Trust of origin. It is, of course, possible to weight the SOSCARE derived records BY BOARD to achieve the totals in the hospital census column and this has been done as part of the sensitivity tests reported in section 10.

Because of missing data on severity throughout the hospital data, the Northern Ireland average distributions of severity of clients in hospital have had to be applied (by age) to the 390 cases in the dataset. Numbers of patients (by Trust) are shown in Table 3. The age and severity breakdown is discussed later.

Details of people admitted to hospital for short-term assessment and treatment were not available from the prevalence study in a form that could be included in the modelling. The prevalence study estimate of overall numbers in this type of care was based on a snapshot of hospital admissions records. It found that approximately 150 people were present in LD hospitals with lengths of stay of less than one year.

Table 3: Number of patients per originating Trust and rate per 10,000 of population (Table 6 from Prevalence Report)

Trust	Soscare Records	Rate per 10,000	Long-stay In-patient Number	Rate per 10,000
A&D	74	7.26	N/a	N/a
C&B	42	3.34		
N&M	13	1.49		
SHSSB	**129**	**4.14**	**118^** (Longstone)	**3.79**
Foyle	24	1.48	26	N/a
Sperrin Lakeland	17	1.43	9	
WHSSB	**41**	**1.42**	**39^** (Stradreagh)	**1.30**
Homefirst	56	1.71	N/a	
Causeway	13	1.12		
NHSSB	**69**	**1.55**	**90***	**2.11**
Down Lisburn	41	2.37	N/a	
NW Belfast	76	5.29		
SE Belfast	25	1.24		
UCHT	9	0.60		
EHSSB	**151**	***2.26***	**220***	**3.30**
Combined EHSSB & NHSSB	**220**	***2.01***	***310^*** (Muckamore)	***2.84***
Total NI	**390**	***2.35***	***467***	***2.77***

^ Longstone total includes 5 patients from WHSSB; 5 from EHSSB and 2 from NHSSB; Stradreagh total includes 4 patients from other Boards and Muckamore total includes 9 patients from WHSSB. (Data supplied from

WHSSB – July 2003).

** The apportionment is based on data supplied by EHSSB as at 28th Feb. 2002*

2.3 Data on clients in the community

The prevalence study dataset identified 14273 people receiving care in the community for learning disabilities – a rate of approximately 8.5 persons per 1000 for Northern Ireland as a whole. From Table 4 it can be seen that there are considerable local variations around this average: from 6.7 in South and East Belfast to 10.4 in North and West Belfast. However, with the exception of the differences between the two Belfast Trusts, the range of rates is smaller than one often finds for the many other health and social services, suggesting a reasonable level of standardisation in the criteria for supplying services to people with learning disabilities.

Table 4 Rate of Clients Receiving Services in the Community for Learning Disabilities (by Trust)

Trust	N of clients	Rate per 1000 persons
Armagh&Dungannon	821	8.1
Craigavon&Banbridge	1041	8.7
Newry&Mourne	812	9.1
Sperrin Lakeland	929	7.8
Foyle	1276	7.9
Causeway	927	9.3
Homefirst	2813	8.6
Down&Lisburn	1647	9.5
N&W Belfast	1487	10.4
S&E Belfast	1349	6.7
Ndown&Ards	1171	7.8
	14273	8.5

The age breakdown of those in receipt of services in the community shows a preponderance of young persons (0-19 year olds represent 58% of all clients). There do not appear to be great variations between Trusts in the percentage of clients in each age group (Table 5). However when we express the numbers receiving services as a proportion of the numbers in the population we find that although there is a negative correlation between the rates for 0-19 year olds and 20 year olds and over this correlation is not statistically significant (Table 6). This could suggest that there are differences between Trusts in the extent to which they identify people with learning disabilities in the various age groups, or there are differences in their ability or propensity to provide services to people of different ages.

Table 5 Age Distribution of Clients Receiving Services for Learning Disabilities in the Community (by Trust)

Trust	Aged 0-19	Aged 20-34	Aged 35-49	Aged 50+	All clients
1 Armagh & Dungannon	57.1	22.5	11.0	9.4	819
2 Craigavon & Banbridge	46.9	24.9	14.6	13.5	1012
3 Newry & Mourne	55.5	24.7	11.1	8.7	809
4 Sperrin Lakeland	62.8	17.7	12.0	7.5	909
5 Foyle	60.9	17.9	11.5	9.7	1274
6 Causeway	65.5	18.0	8.9	7.6	923
7 Homefirst	63.9	19.2	10.3	6.6	2792
8 Down Lisburn	58.8	23.7	9.7	7.7	1643
9 N&W Belfast	50.0	26.3	14.7	9.0	1486
10 S&E Belfast	57.2	21.9	11.5	9.5	1331
11 Ulster CHT	54.2	26.6	10.4	8.8	1166
ALL	58.1	22.0	11.3	8.6	14164

Table 6 Rates per 1000 persons in the community of people receiving services for learning disabilities

Trust	Rates per 1000 persons		
	In popln of all ages	Amongst those aged 0-19	Amongst those aged 20&over
Craigavon&Banbridge	8.69	13.17	6.42
Foyle	7.86	14.31	4.61
Armagh&Dungannon	8.05	14.44	5.04
Newry&Mourne	9.09	15.25	6.01
Sperrin Lakeland	7.81	15.28	4.14
S&E Belfast	6.73	15.28	3.79
N&W Belfast	10.36	16.09	7.63
NDown&Ards	7.83	16.32	4.82
Down&Lisburn	9.55	18.23	5.66
Homefirst	8.58	18.91	4.31
Causeway	9.35	21.18	4.51

Corr is 0.-.224 (sig=.5 not signif)

Variations by gender are also considerable as males aged 0-19 are more than twice as likely to be identified as having some learning disabilities than their female counterparts (see Table 7). The same table shows that differences between genders are less for older clients, though the rates for males are always higher than for females.

The differences by age would be surprising if these data strictly related to prevalence. They are less surprising if they reflect differences in the rates of diagnosis and provision of support to clients of different ages: in which case it might not be unexpected to find that a high proportion of diagnostic effort and services are targeted at younger persons.

Table 7 Rates per 1000 people in population of those receiving services in the community for learning disabilities - by age and gender

Gender	Age group 0-19	20-34	35-49	50+
M	20.79	10.44	4.97	2.88
F	10.28	6.59	4.23	2.22

The prevalence study explored various measures of the severity of people's disabilities and needs. For the purpose of the modelling it grouped clients into those with mild/moderate and those with severe/profound disability. Overall, 25.6% of clients receiving care in the community were assigned to the severe/profound group. The proportion in this group varies with age and is lowest for the 0-19s (see Table 8). However, these proportions may reflect the availability or use of residential care if there is a substitution effect between the different types of care.

Table 8 Numbers of clients with different levels of disability – by age

	Extent of disability				Total clients
Client age	**Mild/moderate**		**Severe/Profound**		
0-19	5385	78.6	1468	21.4	6853
20-34	1918	70.5	804	29.5	2722
35-49	985	65.4	522	34.6	1507
50+	788	70.7	327	29.3	1115
All	9076	74.4	3121	25.6	12197

2.4 Combining the community, hospital and residential datasets.

As has been previously mentioned, clients can only be included in the modelling if we have a code for their ward of residence. For clients in residential or hospital care this code must refer to their pre-care address.

The details theoretically available in the three datasets are summarised in Table 9, but specific items are often missing from individual client records.

Table 9 Basic fields in the three datasets

	Code of originating ward	Age and gender	Severity	Responsible Trust
Residential	NO	YES	YES	YES
Hospital	NO	YES	Aggregate figure for NI only	YES
Community	YES	YES	YES	YES

As previously mentioned, the main problem in combining these data is the lack of an originating ward code for hospital and residential clients. As this prevents them being used directly, we shall try to include these cases by weighting up the numbers of clients in the community dataset. The alternative is to ignore both the hospital and residential groups and assume that the geographical, age and severity distribution of clients in the community can be used as a proxy for all clients; though this strategy will be invalidated by any major substitution effect.

The numbers of clients in the different types of care are shown in Tables 10 and 11. Table 11 shows the rates per 1000 in the population for those in community and the rates per 10,000 for those in residential and hospital care. If there were a substitution effect and no distortions due to restricted access or supply, we would expect the correlation between these rates to be negative and significant, whereas it is positive and insignificant. A further test for a substitution effect could examine whether an increased number of severe cases in the community coincided with a lower number of severe cases in hospital and residential care – again if there was substitution we would expect a significant negative correlation. Table 12 presents the figures: the very low correlation coefficient suggests there is no evidence of either a positive or negative association. This result is confirmed by Figure 1: the proportion of clients with severe difficulties in the community plotted against the proportion in hospital and residential care. The plot demonstrates a strong positive association. This, as well as the results reported in Table 12 could be a product of several factors including: local differences in definitions of severity; differences in diagnostic effort; variations in types of need; historical differences in care policy and the availability of different forms of care; substitution effects associated with variations the availability of care facilities; not to mention possible differences in overall or specific types of access and associated issues of unmet need. Unfortunately, the project cannot pursue or resolve these issues without extensive additional empirical work. Without such work we do not feel it would be appropriate to refer to possible substitution or related effects in interpreting the results of the modelling and, apart from some largely statistical tests for unmet need, do not revisit these issues in the report.

The comparison of the different client groups is pursued in Table 13. Here we examine the age distribution in the different types of care and note that differences are beginning to emerge. The percentage of clients in nursing and residential care aged 35 and over is approximately 80% for most Trusts whereas the corresponding percentage for clients in the community is 20%. We test whether the numbers of older people in community care are related, positively or negatively to the numbers of older people in residential and hospital care. Again the correlation coefficient is very low $r=0.014$ and there is no evidence of an association.

Looking at the patterns of age and severity in the different care settings (Tables 14 and 15), it is clear that the hospital group includes the highest proportion of severe cases, but when added to the residential group, the proportion of severe cases is not much greater than that amongst those in the community.

The tables make it clear that the main difference between these client groups is their age. On average, clients receiving care in the community are younger. This will not surprise professionals working in the field as one of the main reasons for admission to residential care is the difficulty faced by elderly parents caring for adult offspring.

Table 10 Numbers of clients in different types of care (by Trust)

Trust	Ncomm	Nhosp	Nresid	Percent in comm	Percent in hosp & resid	N All
Down&Lisburn	1647	41	129	90.64	9.36	1817
N&W Belfast	1487	76	135	87.57	12.43	1698
NDown&Ards	1171	9	184	85.85	14.15	1364
S&E Belfast	1349	25	267	82.21	17.79	1641
Causeway	927	13	141	85.75	14.25	1081
Homefirst	2813	56	241	90.45	9.55	3110
Armagh&Dungannon	821	74	81	84.12	15.88	976
Craigavon&Banbridge	1041	42	120	86.53	13.47	1203
Newry&Mourne	812	13	152	83.11	16.89	977
Foyle	1276	24	113	90.30	9.70	1413
Sperrin Lakeland	929	17	140	85.54	14.46	1086

Table 11 Rates of clients in community and residential+hospital care

Trust	N in comm per 1000	N in hosp & resid Per 10000
Down&Lisburn	9.547	9.85
N&W Belfast	10.360	14.70
NDown&Ards	7.829	12.90
S&E Belfast	6.733	14.57
Causeway	9.350	15.53
Homefirst	8.581	9.06
Armagh&Dungannon	8.049	15.20
Craigavon&Banbridge	8.693	13.53
Newry&Mourne	9.086	18.46
Foyle	7.864	8.44
Sperrin Lakeland	7.810	13.20

Pearson Correlation 0.128809 Sig. (2-tailed) 0.705838

Table 12 Percentages of clients recorded as having severe/profound disabilities

Trust	Percent Severe in comm	Percent in nurs & resid
Down & Lisburn	33.2	9.36
North & West Belfast	32.7	12.43
North Down & Ards	11.0	14.15
South & East Belfast	40.3	17.79
Causeway	23.7	14.25
Homefirst	26.1	9.55
Armagh & Dungannon	22.9	15.88
Craigavon & Banbridge	26.4	13.47
Newry & Mourne	21.0	16.89

Foyle	18.4	9.70
Sperrin Lakeland	9.6	14.46
	corr (sig=.998)	R=0.001

Table 13 Age breakdown of clients in hospital and residential care (and comparable figures for 35s and over receiving care in the community)

	Percentage in H+R of these ages 0-19	20-34	35-49	50+	Percent H&R aged 35+	Percent comm aged 35+
Down & Lisburn	1.8	13.5	35.3	49.4	84.7	17.5
North & West Belfast	3.4	12.1	35.9	48.5	84.5	23.7
North Down & Ards	5.8	31.7	38.6	23.8	62.4	19.2
South & East Belfast	0.3	18.8	25.7	55.1	80.8	21.0
Causeway	5.2	14.9	29.2	50.6	79.9	16.5
Homefirst	4.2	17.4	35.4	43.1	78.5	16.9
Armagh & Dungannon	0.0	14.2	36.8	49.0	85.8	20.4
Craigavon & Banbridge	4.5	19.4	28.4	47.7	76.1	28.2
Newry & Mourne	2.4	15.2	43.3	39.0	82.3	19.8
Foyle	2.2	5.2	35.1	57.5	92.5	21.2
Sperrin Lakeland	0.0	15.9	36.3	47.8	84.1	19.5
All nursing & resid	2.7	16.7	34.2	46.4	80.6	19.9

Table 14 Age and Severity breakdown of long-stay in-patients (N=415)

Age	Moderate	Severe/ Profound	Total
0-19	0.0%	0.8%	0.8%
20-34	5.8%	12.4%	18.2%
35-49	13.9%	25.4%	39.3%
50+	13.6%	28.1%	41.7%
Total	33.3%	66.7%	100.0%

Table 15 Age and Severity breakdown of those in residential care (N=1671)

Age	Moderate	Severe/ Profound	Total
0-19	1.7%	1.0%	2.8%
20-34	10.1%	6.1%	16.3%
35-49	20.7%	12.6%	33.3%
50+	29.5%	18.1%	47.6%
Total	62.1%	37.9%	100.0%

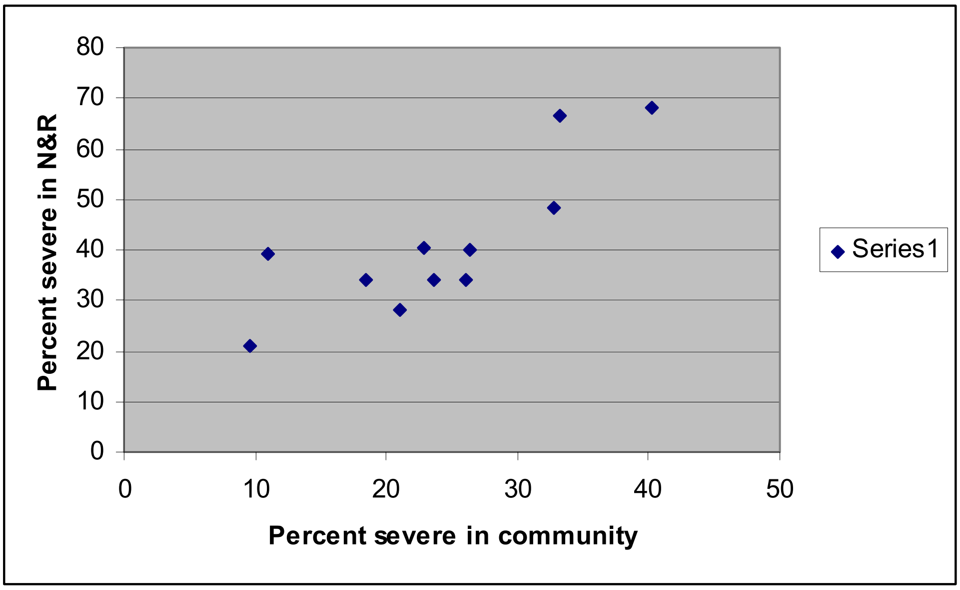

Figure 1

In the light of these comparisons, we will explore several different approaches to the three datasets.

(1) Only include the clients in the community

The question here is whether the geographical, age and severity distribution of clients in the community can be used as a proxy for the distributions for all clients. The main concern is that clients in community and those in residential and hospital care differ in age and severity.

(2) Weight up the clients in the community (by age and sex) at Trust level to take account of the clients in residential and hospital care.

This should give the correct age and sex distribution for clients in each Trust, but has to assume that the hospital and residential; groups have the same originating wards as those in community care. This does not seem to be an unrealistic assumption.

(3) Weight up the clients in the community (by age and sex <u>and severity</u>) to take account of the clients in residential and hospital care.

This is identical to the second option but also tries to correct for the problem that those in residential and hospital care have rather different patterns of severity (with age) to those in the community. The problem with this approach is that it not only makes the same geographical assumptions as the previous option, but because of the limitations of the hospital dataset has to apply a Northern Ireland average distribution of severity (by age) for those in hospital care.

Table 16 Age breakdown of combined (weighted-up) dataset

Trust	**0-19**	**20-34**	**35-49**	**50+**	**All ages**
Down & Lisburn	971	414	220	211	1816
North & West Belfast	751	417	294	237	1699
North Down & Ards	646	373	195	150	1364
South & East Belfast	772	350	230	289	1641
Causeway	616	190	127	148	1081
Homefirst	1811	592	395	312	3110
Armagh & Dungannon	469	206	147	153	975
Craigavon & Banbridge	496	290	198	219	1203
Newry & Mourne	455	226	162	135	978
Foyle	780	235	194	203	1412
Sperrin Lakeland	584	190	168	144	1086
All	8351	3483	2330	2201	16365

After weighting-up the community dataset, the age breakdown of clients is as shown in Table 16. This now takes account of the residential and long-stay hospital cases, which have been given the same geographical distribution as clients in community care. We have some reservations about the method of weighting – though this is the best we could do with the data to hand (the method of weighting is described in more detail in Annex 2). We have one further concern: that the recent focus on detecting learning disabilities amongst young people, and caring for them in the community, may mean that by combining the three datasets we are mixing several different phenomena and creating a dataset that is difficult to model.

3. Data requirements for small area modelling

3.1 Introduction

As described above, the basic aim of the exercise is to model levels of service activity against the socio-economic characteristics of the areas from which the recipients of the services originate. If activity is regarded as a proxy for need, the relation between activity and area characteristics can be used as a model to predict need and, hence, to allocate resources consistent with need.

The study has to address several problems with this approach, especially the assumption that current activity is a proxy for need. Firstly, for a variety of reasons, local service providers may provide different levels of service to the same client groups (especially where provision is non-mandatory). They may also provide services in different ways, which will have cost implications. Access to, and availability of services outwith the activity data may also have an impact on the uses or need for the designated service. For example, the availability of in-patient health care facilities may have an impact on the need for health and social services to provide care in the community.

Moreover, it is widely argued that some need for most health and social services goes unmet and that unmet need is not evenly distributed across the population. The most common positions are that services are most likely to fail to meet the needs of people in the most deprived and most rural areas. If such arguments are valid, current activity data will understate the needs of such populations and some independent measure of need (possibly survey based) may be required as an adjustment.

Finally, there is the problem of what set of areas to use in the modelling. This is potentially problematic as the populations of the areas must be sufficiently small to be socio-economically distinctive, but sufficiently large to give robust estimates of both activity and needs drivers.

These problems and proposed solutions are summarised in Table 17.

Table 17 Potential problems for the modelling – and possible solutions

Potential problem	Possible solution
Differences between Trusts in patterns or levels of service delivery	Dummy Trust variables
Supply of other types of services	Include variables measuring access to other services and tests for endogeneity of these variables
Unmet need in certain types of areas	Consider/apply unmet need adjustments
Area base too small for reliable estimates of activity	Use combinations of wards to ensure no area in modelling has population of less than 2000

The questions of how to introduce Trust level dummy variables and test for supply side effects are considered at appropriate points in the description of the modelling; as is the issue of unmet need. The next section of the report provides a short note on the choice of small areas for the modelling.

3.2 The development of synthetic wards for the modelling

As previously noted, a key requirement for the modelling is to choose areas that are sufficiently large to have robust values for the activity data and socio-economic indicators but not so large that they each contain a variety of conditions and thereby obscure any relations between activity and conditions.

Electoral wards are the obvious choice for this work as Census and administrative statistics are available at this level, but rural wards may have populations that are too small to generate robust values for indicators of conditions and service activity. We considered using the next larger group of administrative units, District Electoral Areas, but tests with both census values and deprivation indicators have shown them to be socially heterogeneous and unlikely to produce conclusive models. Hence we felt we had no alternative but to construct a new set of "synthetic wards". Previous modelling had relied on a set of synthetic wards based on the 1984 ward configurations, but current Census and administrative statistics are mostly based on 1992 wards, which had to be the basis for our new synthetic wards.

In devising these wards, the aim was to produce areas with populations that are always greater than 2000 persons. The algorithm to produce these was based on the grid references of ward population centroids (computed from the postcodes of GP registrations). Wards with populations under 2000 were combined with the nearest ward that was not already part of a synthetic ward. Using these criteria, and a subsequent manual check for the coterminosity of combined wards, we reduced the 582 wards (based on 1992 boundaries) to 524 synthetic wards. A final set of checks ensured that no synthetic wards crossed LHSCG boundaries. The minimum population of these synthetic combinations is 2026 and the maximum is 9572 with a mean of 3216. Of the 524 synthetic wards, 473 are uncombined wards with the same boundaries as the 1992 wards, 44 are combined with one other ward and 7 with two other wards. The numbers of synthetic wards, and their average populations in each Trust, are shown on Table 18. The average ward populations range from 2500 to 3500 in all except the two Belfast Trusts.

Table 18 Numbers of synthetic wards – and average ward populations (by Trust)

	N synth wards	**Popln**	**Av pop per ward**
Armagh&Dungannon	39	101963	2614
Causeway	33	99196	3006
Craigavon&Banbridge	41	119760	2921
Down&Lisburn	53	172482	3254
Foyle	51	162267	3182

Homefirst	109	327762	3007
N&W Belfast	27	143491	5314
NDown&Ards	48	149629	3117
Newry&Mourne	31	89338	2882
S&E Belfast	47	200361	4263
Sperrin Lakeland	45	118935	2643
Total	524	1685184	3216

4. Constructing measures of activity for use as dependent variables in the modelling

4.1 Computing the number of clients originating from each area

The purpose of creating synthetic wards was to reduce the number of areas with such small populations that the estimates of activity and socio-economic characteristics might be unreliable. The tactic was successful in that none of the 524 synthetic wards had zero activity, none generated less than 5 clients and there was an average of 24.3 clients per ward. More than half of the wards had client numbers between 16 and 45. The maximum number of community clients per ward is 147, but we do not treat this as an outlier as it is a large ward with by no means the highest rate of clients per head of population.

Table 19 Distribution of community client numbers by synthetic wards

Numbers of clients	Numbers of synth wards	Percent of synth wards
5 to 15	141	26.91
16 to 25	199	37.98
26 to 45	149	28.44
46 and over	35	6.68
All	524	100

The most basic measure of activity is the number of clients per head of population. Two refinements are often applied to this measure:

- where the activity (or underlying phenomenon) is not evenly distributed across gender and age groups the rate may be standardised by age and sex; and
- where there is information on the services received or severity of the need, rather than just the number of clients, this may be used to weight the client numbers.

4.2 Age-sex standardisation

Tables 7 and 8 (inter alia) have shown that there is a strong relation between activity rates and age and sex and hence a need for age-sex standardisation. We have chosen to standardise by sex and the four age groups used in reporting the prevalence study. These groupings are fairly crude, but robust. Standardised activity rates are computed for both the community and combined datasets. The approach to standardisation is indirect: the dependent variable is computed as the ratio of the actual over the expected client numbers for each ward. The alternative, direct standardisation, adjusts the actual client numbers by the differences between the ward and the national age-sex distributions. With small numbers of clients this tends to be less robust than the indirect method.

4.3 Taking account of severity

The problem with modelling client numbers (rather than service cost) is their failure to take account of variations in individual need. We have tried to correct for this by using the measure of dependency developed by the prevalence study that assigns clients to one of two groups: mild/moderate or severe/profound.

The prevalence project ran a workshop to get professional views on the cost of services required by people of different ages at these two levels of dependency.

The method can be followed by examining the worksheets that were presented to the workshop groups – examples are shown on the next two pages. The data from the prevalence studies and budget lines from the FR22s were used to compile these worksheet summaries of the age-severity profile of clients receiving 12 types of services and the total costs of each service. Services covered included: social work, respite, residential and nursing care, day centres and domiciliary support.

Workshop participants were shown these summaries and asked to estimate the relative service use required by a client in each of the eight groups (defined by 4 age bands and two levels of severity). This was repeated for all 12 services. The results were summed across all services and clients to give an average relative cost for a client in each of the eight groups. The results are shown in Table 20. The merit of this approach is that the resulting weights are applicable to all clients, regardless of the care setting. Hence a cost weight can be applied to every client in the small area modelling, without needing extensive details of the services they receive, provided their age and severity group is known.

There are a number of potential drawbacks, not least the following:

- Recommending weights is difficult without more specific guidance on care settings. For example, would the social worker input to clients with severe disabilities differ if the client was in a community or residential setting? The workshop participants were presented with a hypothetical task: to suggest a figure that was relevant to all settings.
- The workshop generated overall average figures for all clients in Northern Ireland, but there may be variations between Trusts and Boards in the relative care use and provision for the different groups.
- There was some variance in the estimates from workshop participants.
- Because the weights are intended to cover all clients in all settings, they are not specifically intended to apply to clients in the community – and it may be inappropriate to apply them to the dataset that only consists of clients in the community.
- The method relies on having standard criteria for defining severity and there is some evidence (documented in the report on the prevalence dataset) that criteria are locally variable.

Nevertheless, the cost weights provide the only means to hand for taking severity into account without needing detailed information on individual care. Given the above concerns it is important to be sure that the results of the modelling are not overly sensitive to variations in the weights. Sensitivity tests can be undertaken using different sets of weights, or more simply, we can compare the allocations based on models using the recommended weights with those based on modelling of client numbers.

Domicillary

Information

This sheet shows the age and severity profile of patients in this care setting - and the selected quantum of spending.
The challenge is divide this quantum amongst the cells - by inputting a relative cost weight for each cell.

YOUR TASK:

Think about the AVERAGE relative resource use PER PATIENT in this care setting. E.g. Would an average patient in the 50+ category with a profound disability consume 50% more resources than same in the moderate category? Estimates only required.
The fact that there are more or less number of patients in different groups should be ignored.
Input your weights in the **white cells.**

Selected service cost £4,800,000 p.a.

Table 1: Profile of population receiving domicillary services

Age Group	Moderate	Severe / Profound	Total
0-19	21.0%	8.4%	29.4%
20-34	18.9%	10.5%	29.4%
35-49	17.3%	5.8%	23.1%
50+	14.4%	3.7%	18.1%
Total	71.6%	28.4%	**100%**

Table 2: User defined COST WEIGHTS per user

Age Group	Moderate	Severe / Profound
0-19	1.0	2.0
20-34	1.0	2.0
35-49	1.0	2.0
50+	1.0	2.0

Table 3a: Split of resource budget using cost weights input

Age Group	Moderate	Severe / Profound	Total
0-19	785,561	627,119	1,412,680
20-34	704,880	784,303	1,489,183
35-49	647,784	433,862	1,081,646
50+	537,252	279,239	816,490
Total	2,675,476	2,124,524	**4,800,000**

Table 3b: Percentage resource use

Age Group	Moderate	Severe / Profound	Total
0-19	16.4%	13.1%	29.4%
20-34	14.7%	16.3%	31.0%
35-49	13.5%	9.0%	22.5%
50+	11.2%	5.8%	17.0%
Total	55.7%	44.3%	**100.0%**

Social work time

Information

This sheet shows the age and severity profile of patients in this care setting - and the selected quantum of spending.
The challenge is divide this quantum amongst the cells - by inputting a relative cost weight for each cell.

YOUR TASK:

Think about the AVERAGE relative resource use PER PATIENT in this care setting. E.g. Would an average patient in the 50+ category with a profound disability consume 50% more resources than same in the moderate category? Estimates only required.
The fact that there are more or less number of patients in different groups should be ignored.
Input your weights in the **white cells.**

Selected service cost £5,800,000 p.a.

Table 1: Profile of population in reseipt of social work support

Age Group	Moderate	Severe / Profound	Total
0-19	37.6%	11.2%	48.8%
20-34	15.6%	6.6%	22.2%
35-49	9.3%	5.7%	14.9%
50+	9.1%	5.0%	14.1%
Total	71.5%	28.5%	**100%**

Table 2: User defined COST WEIGHTS per user

Age Group	Moderate	Severe / Profound
0-19	2.0	2.0
20-34	1.5	1.0
35-49	1.5	1.0
50+	1.5	1.5

Table 3a: Split of resource budget using cost weights input

Age Group	Moderate	Severe / Profound	Total
0-19	2,589,377	775,169	3,364,546
20-34	804,266	228,109	1,032,375
35-49	480,427	195,014	675,441
50+	468,767	258,871	727,638
Total	4,342,837	1,457,163	**5,800,000**

Table 3b: Percentage resource use

Age Group	Moderate	Severe / Profound	Total
0-19	44.6%	13.4%	58.0%
20-34	13.9%	3.9%	17.8%
35-49	8.3%	3.4%	11.6%
50+	8.1%	4.5%	12.5%
Total	74.9%	25.1%	**100.0%**

Table 20 Service cost (volume) associated with different age and severity groups (from Prevalence Study)

Age	Level of severity	
	Mild/moderate	Severe/Profound
0-19	1.0	1.8
20-34	2.4	4.6
35-49	3.2	5.8
50+	3.2	4.9

When the weights in Table 20 are applied to the community and combined datasets they produce the weighted age-sex utilisation rates shown in Table 21 (these may be compared with the unweighted rates in the same table). One of the more striking features of the comparison is the difference between the figures for men aged 20-34. In the unweighted figures they have a rate that is only half of that in the younger age group, but when the relative severity is taken into account, their rate increases above that for the younger group.

Table 21 Rates per 1000 people in population of those receiving services for learning disabilities – summary of four variables used in the modelling

	Males				Females			
Combined dataset	**0-19**	**20-34**	**35-49**	**50+**	**0-19**	**20-34**	**35-49**	**50+**
Unweighted (nwstdep1)	21.1	11.69	7.34	5.02	12.08	8.15	6.03	4.16
Cost weighted (nwstdep4)	23.35	36.21	33.27	19.49	14.33	25.71	27.06	15.86
Community data								
Unweighted (stdep1)	20.79	10.44	4.97	2.88	10.28	6.59	4.23	2.22
Cost weighted (stdep4)	19.81	27.74	19.48	9.92	10.43	17.8	15.93	7.37

Standardised client rates, both weighted and unweighted, have been computed for both the community and combined datasets. The names of these variables are listed in Table 22 and their intercorrelations are shown in Tables 23 and 24.

Table 22 Naming of standardised activity (dependent) variables

	Community data only		Combined dataset	
Age group	**Unweighted**	**Weighted**	**Unweighted**	**Weighted**
All clients	STDEP1	STDEP4	NWSTDEP1	NWSTDEP4
Clients aged 0-19	STDEP2	STDEP5	NWSTDEP2	NWSTDEP5
Clients aged 20 and over	STDEP3	STDEP6	NWSTDEP3	NWSTDEP6

Looking at the correlations between the community based variables in Table 23, it can be seen that most are highly related, suggesting they are measuring the same phenomenon. The lower correlations between the age restricted variables (for example: stdep2 with stdep3 and stdep6) confirm that the pattern of service distribution to older people may not be the same as that for 0-19 year olds. Though the differences are not so great as to remove the statistical significance of the correlations.

The correlations between the all-age weighted and unweighted versions of the community and combined datasets (in Table 24) suggest that, despite the weighting, these two datasets are very similar and likely to produce similar models.

Because of these similarities, we shall limit much of our presentation of the descriptive statistics to the dataset based on the clients in the community.

Table 23 Correlations between standardised activity variables

		STDEP1	STDEP2	STDEP3	STDEP4	STDEP5
STDEP2	Pearson Correlation	0.820				
	Sig. (2-tailed)	0.000				
STDEP3	Pearson Correlation	0.738	0.227			
	Sig. (2-tailed)	0.000	0.000			
STDEP4	Pearson Correlation	0.819	0.422	0.906		
	Sig. (2-tailed)	0.000	0.000	0.000		
STDEP5	Pearson Correlation	0.732	0.815	0.286	0.560	
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	
STDEP6	Pearson Correlation	0.698	0.221	0.944	0.963	0.321
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000

Table 24 Correlations between community and combined variables

		STDEP1	STDEP4	NWSTDEP1
STDEP4	Pearson Correlation	0.819		
	Sig. (2-tailed)	0.000		
NWSTDEP1	Pearson Correlation	0.982	0.861	
	Sig. (2-tailed)	0.000	0.000	
NWSTDEP4	Pearson Correlation	0.804	0.942	0.868
	Sig. (2-tailed)	0.000	0.000	0.000

4.4 Ward distributions of the activity variables

The distribution of the values of the six (community based) standardised dependents across the 524 synthetic wards is shown in Table 25. From the far right column in this table it can be seen that several wards have zero values for one or more of these variables. This can be a problem if the dependent is to be logged, but in this case does not present a major difficulty as the modelling will concentrate on the first and fourth variables (those relating to the full client base) and will tend to only use the others for sensitivity testing.

Table 25 Summary of synthetic ward values of standardised activity variables

	Clients covered	Min	Max	Mean	Std dev	Wards with zero values
STDEP1	All ages (unwted)	0.230	3.144	0.933	0.395	0
STDEP2	0-19 (unwted)	0.000	2.681	0.928	0.487	2
STDEP3	20& over(unwted)	0.097	6.063	0.951	0.541	0
STDEP4	All ages (wted)	0.046	5.808	0.937	0.517	0
STDEP5	0-19 (wted)	0.000	2.879	0.916	0.501	5
STDEP6	20& over(wted)	0.000	7.843	0.949	0.645	2

5. Needs drivers for learning disability services

As this project is one of three concurrent projects which model services for different Programmes of Care, we had an interest in constructing a set of potential needs drivers that could be used across all the projects.

One starting point was to include variables relating to the nine equality groups, viz:

Gender
Age
Marital Status
Ethnic Origin
Religion
Whether dependents or not
Whether disabled or not
Political Opinion
Sexual Orientation.

Understandably, we also wanted to include variables specific to learning disabilities. From the epidemiological and medical literature, it appears that learning disabilities can be associated with many medical conditions and may in part be caused or exacerbated by social and environmental factors. A report from the Welsh Learning Disabilities Sub-Group notes that "upward pressures on the incidence of learning disabilities include:

- increases in maternal age (associated with higher risk factors for some conditions associated with learning disability, such as Down's syndrome);
- improved survival of "at-risk" infants, such as low-birth weight infants, due to improved health care;
- increases in more recently significant pre-natal threats such as HIV infection and substance abuse;
- an increase in the proportion of children growing-up in poverty".

Epidemiological analyses of the correlates of the incidence of learning disability cite different factors depending on the level of disability. Some of the more significant correlates of mild learning disability are social and environmental factors such as parental socio-economic group, family structure and stability (Birch et al, 1970);

whereas the main determinant of severe learning disabilities are biological, often pre-natal (Fryers (1993).

A more recent study in Wales (Morgan et al 2000a and 2000b) reported that the distribution of people with a learning disability correlated significantly with deprivation and that the presence of a learning disability hospital significantly affected secondary care uptake. In a second report (Morgan et al 2000b) based on the same sample (people in S Glamorgan HA with a secondary care contact between 1991 and 1997) the authors found a positive correlation between the prevalence of people with both learning disabilities and epilepsy and the Townsend score of deprivation. While this analysis is based on people with secondary care contacts who might be assumed to have more severe symptoms, there is widespread support amongst social service departments that the prevalence of levels of LD that requires social services support is associated with deprivation. Hence various indicators of different types of deprivation are included in the list of need drivers.

Given the high proportion of 0-19 year olds in the dataset from the prevalence study, we have decided to also include some variables that predominately relate to children. However, we have been unable to include some relevant variables, such as low birth weight, as these are not available at ward level. *(Low birth weight would normally be available at this level, but new figures were being compiled during the course of the project and were not ready in time for the modelling).*

A great deal of effort went into the construction of the dataset of potential needs drivers for the modelling – parts of which will also be used for the Physical and Sensory Disability and Family and Childcare Work. It contains 81 variables of which the majority are derived from small area data from the 2001 Census, though there are also a number of indicators based on claimant counts and other administrative sources. A full list of the variables and their distributional properties can be found in Annex 1. Broadly speaking they fall into four groups.

General deprivation and social structure

The literature on the distribution of learning disabilities posits a relationship with deprivation, though there is not a substantial body of evidence to support this link. Nevertheless, we considered the inclusion of a variety of both Census and administrative data based measures of deprivation as a priority. The variables chosen included measures of (and proxies for) low income as well as indicators of housing conditions. We also included several measures of social structure, such as one-parent households that that are often associated with material deprivation.

Illness and general morbidity

The morbidity variables are based on self-report data from the census. Standardised Mortality Ratios (SMRs) are also included in the dataset.

Child deprivation and circumstances of families with children

A selection of these variables was included because of the high proportion of young people receiving services for learning disabilities.

Educational attainment of the population

The 2001 Census recorded that approximately 42% of the population of Northern Ireland aged 16-64 had no educational qualifications. While many of the 0.9% of the population receiving services for learning disabilities may never acquire educational qualifications it seems tenuous to argue that areas with lowest educational attainment will also include the highest rates of people with learning disabilities. Nevertheless, rates of people without educational qualifications proved to be one of the best predictors of services to people with learning disabilities and this, and several other variables relating to education, were included.

Population density

There has been extensive debate on the role of measures of population density and sparsity in resource allocation formulae. The pressure to include some measure of sparsity tends to come from rural authorities who judge that there will be extra costs in providing some types of services to sparsely distributed populations. Even where there is clear evidence of these extra costs, our argument is that they should be addressed by specific weightings rather than by attempts to include sparsity in an allocation formula. The problem with the formulaic approach is that in most areas of the UK, sparsity is strongly and negatively correlated with deprivation – because the greatest deprivation is usually found in the densest parts of metropolitan areas. Hence any measure of density will tend to serve as a proxy for urban deprivation and direct money away from rural areas. For this reason we are reluctant to include measures of sparsity or density directly in the modelling, but we recognise two concerns:

- there may be extra costs of service delivery in rural areas; and
- there may be unmet need in (rural) areas with limited access to services or difficulties of supply.

We think that the former should be addressed with targeted cost weights. The latter could be considered when the unmet needs adjustment is applied to the final formulae, but the recommended test and adjustment encounters similar problems to those described above – that it cannot prevent measures of density acting as inverse measures of deprivation.

6. Preliminaries to the modelling

6.1 Correlations with need drivers

The starting point for our statistical analysis is the raw correlations of each of the 'candidate' needs variables with the utilisation measures: the weighted and unweighted standardised variables (STDEP4 and STDEP1 for the community dataset and NWSTDEP4 and NWSTDEP1 for the combined). These are shown in Tables 26 and 27. Definitions of the potential needs drivers can be found in Annex 1.

There are several distinctive features of these tables, firstly the number of variables that are relatively highly correlated with the service activity; secondly, the differences between correlates of the two dependent variables.

The unweighted client rate variable (stdep1) is strongly correlated with many of the variables in the dataset. In particular, there are highly significant and positive correlations with measures of the following:

- population educational attainment
- housing tenure (social rental) – for both adults and children
- socio-economic group
- self-report general health
- household structure – incl. lone parents and persons who are single, widowed or divorced
- claimant counts, such as income support and working family tax credit
- proxies for low income (no car).

The same groups of variables are strongly correlated with the all-age weighted dependent (stepd4), though the relative strengths of the correlations are slightly different (Table 27).

Table 26 Correlations with (community based) unweighted dependent (STDEP1)

Need driver	Pearson Correlation	Sig. (2-tailed)	Need driver	Pearson Correlation	Sig. (2-tailed)
NOQUAL	0.520	0.000	KOWCRAA	0.328	0.000
SOCREN	0.514	0.000	SOCENVSC	0.316	0.000
KSOCRENB	0.502	0.000	KNGH	0.279	0.000
CHILDPSC	0.500	0.000	KNOCENTH	0.274	0.000
ADLLTI	0.494	0.000	SINGLE	0.260	0.000
LOWSEG	0.485	0.000	ADIS65OV	0.259	0.000
EDUCSC	0.485	0.000	KJAS	0.244	0.000
KSOCRENA	0.480	0.000	ALLSMR	0.240	0.000
ADNGH	0.474	0.000	NOCENTH	0.234	0.000
KNOCARC	0.474	0.000	NWRDS	0.139	0.001
KNOCARB	0.471	0.000	CATHOL	0.087	0.047
NOCARER	0.467	0.000	HH3K	0.086	0.050
NOCAR	0.465	0.000	KCATHOL	0.066	0.130
LLTI	0.463	0.000	KNBASIC	0.051	0.241
ADIS1864	0.459	0.000	HOUSSC	0.040	0.366
KNOCARA	0.457	0.000	KLPP	0.024	0.581
KIS	0.455	0.000	NOBASIC	0.018	0.675
NGHS	0.453	0.000	HHALLK	-0.014	0.747
LPDEPK	0.451	0.000	KPRVRENA	-0.019	0.658
KDLA	0.446	0.000	KPRVRENB	-0.020	0.650
ADIS	0.442	0.000	HHDEPK	-0.045	0.306
INCSC	0.441	0.000	SNGCARER	-0.046	0.297
LONPU24	0.438	0.000	PRIVREN	-0.047	0.284
OVSC	0.438	0.000	PROTST	-0.080	0.067
ADDLA	0.434	0.000	KPROT	-0.084	0.055
KLOWSEGB	0.432	0.000	PRIVREM	-0.105	0.016
SWIDRCD	0.421	0.000	NONWHT	-0.151	0.001
EMPSC	0.420	0.000	ACCSSC	-0.182	0.000
ADLPP	0.419	0.000	THREECAR	-0.319	0.000
U65SMR	0.415	0.000	KOWNOCCA	-0.361	0.000
KLOWSEGA	0.412	0.000	KTWOCARA	-0.391	0.000
KLLTI	0.411	0.000	KTWOCARB	-0.395	0.000
U75SMR	0.410	0.000	KTWOCARC	-0.404	0.000
ADUNEMP	0.408	0.000	MARRIED	-0.434	0.000
ADJSA	0.396	0.000	TWOCAR	-0.438	0.000
EXMAR	0.394	0.000	HIGHSEG	-0.458	0.000
PROPNST	0.393	0.000	KHGHSEGB	-0.461	0.000
HLTHSC	0.392	0.000	OWNOCC	-0.462	0.000
KWFTC	0.390	0.000	KHGHSEGA	-0.470	0.000
KOWCRAB	0.377	0.000	KOWNOCCB	-0.480	0.000
ADWFTC	0.343	0.000			

Table 27 Correlations with (community based) weighted dependent (STDEP4)

Need driver	Pearson Correlation	Sig. (2-tailed)	Need driver	Pearson Correlation	Sig. (2-tailed)
ADDLA	0.488	0.000	KWFTC	0.284	0.000
ADLLTI	0.485	0.000	PROPNST	0.284	0.000
NOCARER	0.461	0.000	SINGLE	0.282	0.000
ADIS1864	0.460	0.000	SOCENVSC	0.273	0.000
ADNGH	0.454	0.000	ADWFTC	0.273	0.000
ADIS	0.454	0.000	ALLSMR	0.256	0.000
CHILDPSC	0.454	0.000	KNGH	0.256	0.000
NOQUAL	0.453	0.000	CATHOL	0.220	0.000
LOWSEG	0.452	0.000	KJAS	0.219	0.000
OVSC	0.442	0.000	KNOCENTH	0.201	0.000
INCSC	0.439	0.000	KCATHOL	0.195	0.000
LLTI	0.437	0.000	NOCENTH	0.190	0.000
KLOWSEGB	0.434	0.000	HH3K	0.162	0.000
EMPSC	0.432	0.000	KNBASIC	0.129	0.003
KNOCARB	0.425	0.000	NOBASIC	0.083	0.057
KOWCRAB	0.422	0.000	HHALLK	0.076	0.081
NGHS	0.421	0.000	HOUSSC	0.069	0.117
KLOWSEGA	0.421	0.000	NWRDS	0.050	0.256
KNOCARA	0.419	0.000	KPRVRENA	0.048	0.273
KIS	0.417	0.000	HHDEPK	0.028	0.519
KNOCARC	0.415	0.000	KPRVRENB	0.022	0.611
SOCREN	0.414	0.000	KLPP	0.018	0.673
KSOCRENA	0.413	0.000	SNGCARER	0.013	0.762
ADLPP	0.404	0.000	PRIVREN	-0.034	0.431
ADUNEMP	0.403	0.000	PRIVREM	-0.075	0.085
KOWCRAA	0.400	0.000	ACCSSC	-0.141	0.001
KSOCRENB	0.398	0.000	NONWHT	-0.166	0.000
U75SMR	0.397	0.000	THREECAR	-0.211	0.000
HLTHSC	0.396	0.000	PROTST	-0.214	0.000
EDUCSC	0.395	0.000	KPROT	-0.215	0.000
NOCAR	0.393	0.000	KOWNOCCA	-0.251	0.000
LPDEPK	0.391	0.000	KTWOCARA	-0.290	0.000
U65SMR	0.387	0.000	KTWOCARB	-0.292	0.000
KDLA	0.379	0.000	KTWOCARC	-0.304	0.000
EXMAR	0.373	0.000	TWOCAR	-0.340	0.000
SWIDRCD	0.369	0.000	KHGHSEGB	-0.372	0.000
LONPU24	0.368	0.000	KHGHSEGA	-0.380	0.000
ADJSA	0.363	0.000	KOWNOCCB	-0.392	0.000
KLLTI	0.330	0.000	HIGHSEG	-0.398	0.000
ADIS65OV	0.306	0.000	MARRIED	-0.402	0.000

6.2 Supply side factors

As for many health and social services, there is a possibility that the supply of, and access to, services for people with learning disabilities may influence the volume of services used. Ward level measures of access to services are not always easy to obtain or compute, but in this case we were provided with data on two types of relevant services: average travel times from each electoral ward to hospitals with specialised units for learning disabilities and to residential care homes with relevant places. Both sets of times were aggregated to the synthetic ward base and summarised as average and minimum travel times.

Table 28 Synthetic ward values of supply side variables

LDPLMIN – minimum time to home with residential places
LDPLAV – average time to home with residential places
LDHMIN – minimum time to hospital with specialised ward
LDHAV – average time to hospital with specialised ward

	Minimum	Maximum	Mean	Std. Deviation
LDPLMIN	2.23	25.98	7.3077	4.8856
LDPLAV	53.75	147.45	72.2654	17.6131
LDHMIN	2.45	114.50	26.9669	17.5576
LDHAV	43.76	130.83	64.6972	14.5120

Simple correlations between these variables and the six dependents are shown in Table 29. Four points are worth noting. The signs are all negative; the correlations with the average times are generally stronger than those with the minimum; correlations with the severity weighted dependents are stronger than those with the unweighted variables; and, most striking, the correlations are strongest for the dependents limited to the older client group.

From the table it appears that the numbers of people with learning disabilities have negative, weak and generally statistically insignificant correlations with the provision of residential and hospital care. Predictably, the correlations are weakest for the younger clients, who are least likely to be placed in hospital or residential care. Slightly stronger correlations with severity-weighted rates suggest that the availability of residential or hospital places may remove some of the more severe cases from the community, but the evidence is far from conclusive and there are other possible explanations.

Based on the above correlations we propose using the two average times variables in the modelling. We are not particularly happy using the average rather than minimum time variables, as we would expect the latter to be more specific, but suspect that the average variables perform rather better because there are relatively few facilities of this type. We have repeated the modelling both with and without including these variables and have tested for their endogeneity with the need drivers.

Table 29 Correlations between (community based) activity and supply variables

		LDPLMIN	LDPLAV	LDHMIN	LDHAV
STDEP1	Pearson Correlation	-0.054	-0.039	-0.040	-0.075
	Sig. (2-tailed)	0.220	0.369	0.365	0.085
STDEP2	Pearson Correlation	-0.049	-0.005	-0.006	-0.036
	Sig. (2-tailed)	0.263	0.912	0.888	0.414
STDEP3	Pearson Correlation	-0.035	-0.078	-0.078	-0.104
	Sig. (2-tailed)	0.423	0.075	0.075	0.017
STDEP4	Pearson Correlation	-0.063	-0.079	-0.138	-0.131
	Sig. (2-tailed)	0.150	0.072	0.002	0.003
STDEP5	Pearson Correlation	-0.031	0.101	-0.011	0.019
	Sig. (2-tailed)	0.483	0.020	0.795	0.665
STDEP6	Pearson Correlation	-0.063	-0.129	-0.160	-0.163
	Sig. (2-tailed)	0.150	0.003	0.000	0.000

7. The General Approach to the Modelling

The overall approach to the modelling is as follows:

- All possible variables were included in the regression model.
- Variables with both counter-intuitive signs and standard errors greater than their respective coefficients were eliminated. In the initial stages, due to the large number of variables, two or three variables were deleted at each re-estimation of the model.
- Variables with counter-intuitive signs irrespective of their significance level were rejected.
- Variables with intuitively correct signs were rejected on the basis of lack of statistical significance (selection criteria: $p>0.05$). At each re-estimation of the model any variables resulting in counter-intuitive signs were eliminated prior to searching for non-significant variables.
- where the model appeared to be too narrowly based, attempts were made to “force” variables relating to other types of phenomenon into the equation.
- modelling was repeated with and without the inclusion of the two supply side variables.
- the supply side variables were tested for endogeneity with the need drivers in the final models.
- variables relating to phenomenon not covered by variables already in the model were forced into the model when there was evidence of poor specification.
- other strategies used to improve specification included: changing the functional form and testing the influence of outliers.

The recent literature on unmet need rightly raises the point that it is not always easy to decide what is the “correct” or “intuitive” sign of a correlation. Even with careful choice of potential need drivers, multicollinearity is always present to a high degree in these exercises because the variables are heavily intercorrelated. Moreover, without qualitative work and individual level analyses we cannot always say what is the correct sign – especially if there is relatively limited empirical literature on the possible determinants of need and activity. All we can say in the present context is that we have taken account of the, albeit limited, literature in the field; and we have paid continuing attention to problems of multicollinearity. For the latter reason, we have frequently used manual stepwise procedures thus enabling us to test the effects of adding variables individually on the sign and significance of coefficients. By such procedures, especially if one considers variables in small groups as well as individually, one can explore sign changes and their probable cause. The main question is: what do we do when we have a variable whose sign is persistently counter-intuitive? At what point can one regard this as a pointer to unmet need, rather than a problem with the data, or a genuine relation contradicting prior research? These are extremely difficult issues to resolve by purely statistical techniques and generally require further empirical research. Fortunately, the counter-intuitive signs we encountered in the modelling were almost always unstable and patently due to interaction with other variables.

In addition to checking for the implications of multicollinearity, tests were made to ensure that the statistical model was well specified. The specification of a regression model consists of a formulation of the regression equation and of statements or assumptions concerning the regressors and the disturbance term. A "specification error" in the broad sense occurs whenever the formulation of the regression equation or one of the underlying assumptions is incorrect. Specification errors can occur for various reasons:

- omission of a relevant explanatory variable.
- inclusion of an irrelevant explanatory variable.
- incorrect mathematical form of the regression equation.
- incorrect specification of the covariance structure such that the error term is not normally distributed.

Only well-specified models were considered acceptable, as measured by the widely recognised "Reset" test for specification that involves testing the significance of the squared predicted value of the basic model when added to the model as an independent variable. The intention of the modelling procedure was therefore to derive a model of utilisation, which was (i) plausible; (ii) parsimonious; and (iii) statistically acceptable.

Details of the modelling are reported in the next two sections. The first considers the variables derived from the dataset on clients in the community and the second describes the modelling of the variables from the combined dataset.

8. Modelling the variables from the community dataset

This and subsequent sections report the later stages on the modelling. After extensive sifting of the many potential need drivers that have been described in the previous section (and listed in Annex 1), we arrive at the subsets that are reported in the following sections. This preliminary sifting involved a combination of manual and automatic techniques and involved paying continual attention to patterns of multicollinearity.

8.1. Modelling the unweighted dependent

The unweighted dependent was first modelled with the Trust dummies. All but four of the dummies were significant at 5% and the total variance explained is 16.8% (see Table 30). This level of explained variance is similar to previous modelling of services for Family and Child Care and for older people, where the Trust dummies tended to explain 15-20% of the overall variance.

Table 30 Coefficients of Trust Dummies with Unweighted Dependent (STEPD1)

Dummy	Beta	t	Sig.
(Constant)	1.026	28.551	0.000
TRDUMA1	-0.073	-1.655	0.099
TRDUMA2	0.058	1.304	0.193
TRDUMA3	-0.184	-4.086	0.000
TRDUMA4	0.082	1.752	0.080
TRDUMA5	-0.136	-2.934	0.003
TRDUMA7	0.113	2.458	0.014
TRDUMA8	-0.308	-6.695	0.000
TRDUMA9	-0.129	-2.945	0.003
TRDUMA10	-0.150	-3.144	0.002
TRDUMA11	-0.082	-1.816	0.070
Explained variance			16.8%

Adding the potential needs drivers and supply side variables results in a series of models based on a small subset of the variables. The pattern throughout was for the Census based measure of educational non-attainment to be the strongest predictor. This was usually accompanied by several claimant count variables, mainly children in disability living allowance households, children in job seekers households or adults in disability living allowance households. Some measure of limiting long term illness or "not good health" was also significant in most of the models. In an alternative set of models, the claimant count variables were supplanted by an indicator of housing tenure, usually the proportion of households (or households with children) in social rented accommodation. A selection of results from these preliminary models can be seen in Tables 31a-31e. The abbreviations for the variables used in these tables are:

ADLLTI – proportion of adults with limiting long-term illness
NOCENTH – proportion of households with no central heating
KSOCRENA – proportion of children in social rented housing
KJAS – proportion of children in job seekers allowance households
NOQUAL – proportion of persons aged 16-64 with no qualifications
KDLA – proportion of children in disability living allowance households

The correlations between the needs drivers (shown in Table 32) go some way to explaining the substitutability of the variables.
Although all the models in Table 31 have respectable explanatory power (50% or more) they are poorly specified as can be judged by the significance of the Reset test coefficient in Table 31e (these are the predicted values from the model in Table 31d, squared and reinserted into the model as in the standard reset test procedure). The poor specification suggests (amongst other possibilities) problems with outliers, the wrong model form, missing explanatory variables or that the underlying phenomenon may not, in fact, be a single coherent phenomenon.

Table 31 Models with unlogged vars

(dependent is unlogged unweighted standardised client rate (STDEP1)

Needs driver	Beta	t	Sig.
Table 31a			
ADLLTI	0.256	3.250	0.001
NOCENTH	0.070	1.821	0.069
NOQUAL	0.231	3.438	0.001
KSOCRENA	0.188	3.553	0.000
KJAS	0.086	2.165	0.031
Explained variance			51.1%
Table 31b			
ADLLTI	0.140	1.594	0.112

SOCREN	0.161	2.542	0.011
NOCENTH	0.068	1.774	0.077
NOQUAL	0.238	3.503	0.001
KJAS	0.086	2.184	0.029
KDLA	0.171	3.632	0.000
Explained variance			52.0%
Table 31c			
ADLLTI	0.128	1.450	0.148
SOCREN	0.140	2.249	0.025
NOQUAL	0.289	4.681	0.000
KJAS	0.097	2.491	0.013
KDLA	0.171	3.632	0.000
Explained variance			51.8%
Table 31d			
ADLLTI	0.384	5.863	0.000
NOQUAL	0.272	4.390	0.000
KJAS	0.106	2.661	0.008
Explained variance			50.0%
Table 31e			
Reset test var	0.618	3.455	0.001

Table 32 Correlations between Needs Drivers in Tables 31a-e.

		NOQUAL	ADLLTI	KJAS	KDLA
ADLLTI	Pearson Correlation	0.826139			
	Sig. (2-tailed)	9.69E-22	.		
KJAS	Pearson Correlation	0.447003	0.409752		
	Sig. (2-tailed)	9.69E-22	9.69E-22	.	
KDLA	Pearson Correlation	0.503523	0.706519	0.267574	
	Sig. (2-tailed)	9.69E-22	9.69E-22	4.84E-10	.
SOCREN	Pearson Correlation	0.679974	0.828212	0.2978	0.645176
	Sig. (2-tailed)	9.69E-22	9.69E-22	3.42E-12	9.69E-22

Various checks were made to identify the cause of the misspecification. The distribution of the residuals is normal without obvious outliers. Additional variables were forced into the model to try to increase the coverage of income, general deprivation and other dimensions of deprivation, but all these failed to improve the specification.

However, changing the functional form by logging both the dependent and the needs drivers considerably improved the situation and the best specification was obtained from the combination of a logged dependent and unlogged need drivers (as shown in Table 33a).

Our preferred model for the unweighted dependent (Table 33a), passes the reset test with a coefficient for the squared predicted values that is not significant at 5 or 1%. The explanatory power of this model is 50.7%. *(The standard test for mis-specification takes the predicted values from a model and introduces their square as a new variable. If this new variable is significant it is evidence of mis-specification – this is known as the Reset test.)*

Re-running this model with logged needs drivers (the log-log form in Table 33b) results in a Reset test coefficient of 0.126, which is significant at 1.3% and indicates misspecification.

Table 33 Log-lin and log-log forms of preferred model for the unweighted dependent

Needs driver	**Beta**	**t**	**Sig.**
Table 33a LOG-LIN			
NOQUAL	0.373	6.859	0.000
KJAS	0.113	2.862	0.004
LLTI	0.237	4.120	0.000
Reset test	0.029	0.598	0.550
			50.7
Table 33b LOG-LOG			
Reset	0.126	2.486	0.013
LOGLLTI	0.246	4.213	0.000
LOGNOQUAL	0.393	6.381	0.000
LOGKJAS	0.103	2.391	0.017

The Census measure of educational non-attainment is consistently one of the strongest predictors in these models. However because we suspected it may be acting as a proxy for more general forms of deprivation we decided to test the effects of removing it and forcing general measures of deprivation or income deprivation into the model. *(The process of forcing variables into the model simply involves them being included regardless of their significance).* The results can be seen in Tables 34a-c. Substituting the Noble income score for NOQUAL results in statistically insignificant values for the income score coefficient. When one of the other income related variables

(Children in job seekers allowance households (KJAS)) is removed, the Noble income score is still not significant (Table 34b). This income score continues be insignificant when it is included with only one other variable, the proportion of adults with limiting long-tem illness. Much the same happens when measures of general deprivation were either included alongside NOQUAL or substituted for NOQUAL. Ward level correlations of NOQUAL and various deprivation and income measures with rates of learning disability clients within Trusts also point to NOQUAL as the most robust predictor of this set of variables.

Table 34 Attempts to substitute measure of income and general deprivation for the census measure of no-qualifications

Needs driver	Beta	t	Sig.
Table 34a			
ADLLTI	0.531492	7.378835	6.59E-13
NOCENTH	0.116902	3.293886	0.001057
KJAS	0.137179	3.350613	0.000867
KDLA	0.152722	3.176046	0.001584
INCSC	-0.11598	-1.56775	0.117565
Table 34b			
ADLLTI	0.537337	7.388057	6.17E-13
NOCENTH	0.136098	3.847158	0.000135
KDLA	0.151038	3.110011	0.001976
INCSC	-0.06069	-0.83322	0.405112
Table 34c			
ADLLTI	0.599	8.448	0.000
INCSC	0.030	0.417	0.677

Much of the above modelling was repeated with and without the inclusion of the two supply side variables, anticipating the possibility of having to use two-stage least squares if the supply factors were found to be endogenous with the variables in the suggested model. Their inclusion had no effect on the variable selection as the same set of variables were significant whether or not the supply side variables were present. The standardised coefficients for the model with the supply side variables are shown in Table 35.

A formal test for endogeneity was carried out with the models in Table 35. The value of the F test statistic $F(2,500)=2.33$ is not significant at 5%. The supply variables are not endogenous, there is no need to employ two stage least squares and the standard Reset test can be used to test for specification.

Table 35 Models including supply variables

Needs driver	Beta	t	Sig.
LDPLAV	-0.065	-0.390	0.697
LDHAV	0.017	0.157	0.875
NOQUAL	0.375	6.813	0.000
KJAS	0.120	2.982	0.003
LLTI	0.239	4.069	0.000
Explained variance			50.5%

8.2 Modelling the cost weighted variables (from the community dataset).

The same modelling process was repeated with the weighted all-age client variable STEPD4 and its logged form GSTEPD4. Again, the modelling was conducted with and without the two supply side variables, with very similar results. The best model based on a small number of need drivers is shown in Table 36. It has a log-lin form, reasonable explanatory power and is well specified. Examination of the distribution of residuals suggests that specification might be improved even further by excluding the two wards with the lowest activity levels, but these exclusions are not essential as the model is already well-specified. The LOG-LOG model was also poorly specified.

Table 36 Best parsimonious model for logged weighted dependent

Needs driver	Beta	t	Sig.
LDPLAV	0.326	1.956	0.051
LDHAV	-0.168	-1.548	0.122
NOCENTH	0.094	2.395	0.017
NOQUAL	0.415	9.259	0.000
KDLA	0.165	3.980	0.000
Reset coeff	-0.044	-0.984	0.325
Explained variance			49.4%

One of the supply variables is almost significant in this model (Table 36), but when a test for endogeneity is applied the value of F(2,500)=1.06 is not significant. Hence the suggested model is as shown in Table 37.

Table 37 Suggested model for weighted dependent

Needs driver	Unstand coeff	Std dev	Std coeff	t	Sig of t
(Constant)	-0.694	0.036		-19.327	0.000
NOCENTH	0.820	0.307	0.099	2.671	0.008
NOQUAL	0.959	0.096	0.444	10.017	0.000
KDLA	3.231	0.768	0.172	4.208	0.000

We have some concerns at the inclusion of the NOCENTH (households with no central heating) variable in the model as it does not appear to have a direct theoretical relevance to learning disabilities, although it may be a good proxy for aspects of socio-economic conditions not covered by the two other variables. Various alternatives were attempted of which two are shown in Tables 38 and 39. The proportion of households including children in overcrowded conditions failed to be a significant substitute, as did the proportion in social rented housing.

We also considered using the variables in the suggested model for the unweighted dependent. This model is well-specified but has slightly lower explanatory power than the model including the central heating variable (48.8% rather than 49.4%) (Table 40).

Tables 38 and 39 Attempts to replace variable relating to lack of central heating

Needs driver	Beta	t	Sig.
Table 38			
NOQUAL	0.480	11.214	0.000
KOWCRAA	0.044	0.936	0.350
KDLA	0.139	3.200	0.001
Table 39			
SOCREN	0.009	0.173	0.863
NOQUAL	0.482	9.420	0.000
KDLA	0.149	3.303	0.001

Table 40 Using variables from model recommended for the unweighted dependent

Needs driver	Beta	t	Sig.
Table 40a			
LDPLAV	0.323	1.924	0.055
LDHAV	-0.168	-1.534	0.126
NOQUAL	0.443	7.981	0.000
KJAS	0.089	2.192	0.029
LLTI	0.122	2.065	0.039
Explained variance			48.8%

9. Modelling the combined data (including hospital and residential client numbers)

9.1. The Unweighted Variable

The modelling process was repeated using the combined dataset described in section 2.4. As there is no new geographical information on the hospital and residential clients and the variables had proved to be highly correlated with the community based numbers, we expected a similar set of need drivers to emerge, but were unsure of the impact of including the different age and severity patterns of the hospital and residential cases.

In the event, the results of the modelling proved remarkably similar. The same variables were significant and attempts at variable substitution tended to produce the same results, though a few new variables entered.

The variables in the preferred model for the combined model without cost weights can be seen in Table 41. The variable set differs from the community only model in two respects: the proportion of households (with a dependent person without a carer) has replaced the standardised limiting long-term illness variable and the proportion of children in disability living households is included.

With this model, the Trust dummies explain 17.1% of variance and the total variance explained excluding the (insignificant) supply side variables is 50.4%. The best specification is obtained by logging the dependent, but not the independent variables: the t value for the Reset coefficient is –1.302 (significance=0.194); for the fully unlogged model the t value is 12.0 which is highly significant and poorly specified.

Table 41 Variables in recommended model for unweighted combined data

Variables	Beta	t	Sig.
Supply			
LDHAV	-0.070	-0.634	0.526
LDPLAV	0.031	0.183	0.855
Needs drivers			
NOCARER	0.195	2.692	0.007
NOQUAL	0.328	4.780	0.000
KJAS	0.132	3.279	0.001
KDLA	0.181	4.205	0.000

9.2 Combined Model with weighted dependent

The NOCARER variable occurs in most attempts to model the weighted combined dependent – as it does for the unweighted combined variable. NOQUAL and NOCENTH are present, as in the community weighted model. Children in disability living allowance households (KDLA) are strongly significant in most variable combinations. The problematic variable here is the children in job seekers allowance households (KJAS). This is just significant (at 5%) if dummies are used for each Trust, but its significance reduces to 6% if the extra dummies are introduced for Belfast. We have retained the variable to slightly increase the explanatory power of the model, but would be equally happy to recommend its exclusion (in which case the overall r-squared drops by approx 0.003).

Models of the combined weighted dependent have the lowest explanatory power of all the proposed models. The Trust dummies explain 12% of the variance rising to 42% for the full model. The model is well-specified: the Reset test statistic is not significant at 0.285. Again, the supply side variables are not significant.

As for the modelling of the unweighted data, the log-lin form is well specified and the specification improves even further if two low activity outlier wards are excluded. These are 95BB08 and 95BB07: Comber North and East wards in Ards Local Government District.

Table 42 Variables in recommended model for weighted combined data

Variables	Beta	t	Sig.
Supply			
LDHAV	-0.19544	-1.61692	0.106526
LDPLAV	0.249208	1.353608	0.176474
Needs drivers			
NOCARER	0.200787	2.556787	0.010859
NOCENTH	0.118149	2.684283	0.00751
NOQUAL	0.269302	3.48314	0.000539
KJAS	0.081709	1.866726	0.062526
KDLA	0.133983	2.83682	0.004742

10. Testing the models

10.1 Sensitivity tests

The brief set of sensitivity tests mostly concentrated on the effects of removing the data for each of the Boards in turn. (*Here we only report the results for the variables based on the clients in the community – the results for the combined variables are similar.)*

When this test is applied to the models derived from both the weighted and unweighted community variables, the coefficients of all the needs drivers in the model fluctuated but remained significant at least 5% (Table 43a and b).

Table 43a Sensitivity tests – removing one Board at a time (unweighted community model)

Table shows - T test values of standardised coefficients

		Excluding Board			
	All	1 (Eastern)	2 (Northern)	3 (Southern)	4 (Western)
NOQUAL	6.89	5.5	6.6	5.5	6.1
KJSA	2.95	3.2	2.4	2.5	2.1
LLTI	4.16	3.1	2.7	5.2	3.5

All signif at least 5%

Table 43b Sensitivity tests– removing one Board at a time
(weighted community model and replacement model)
Table shows standardised coefficients

		Excluding Board			
	All	1 (Eastern)	2 (Northern)	3 (Southern)	4 (Western)
NOCENTH	.097	.143	.073	.071	.102
NOQUAL	.446	.418	.439	.473	.433
KDLA	.166	.163	.191	.152	.160
NOQUAL	.443	.460	.424	.420	.446
KJSA	.089	.144	.112	.112	.062
LLTI	.122	.072	.131	.131	.119

A further set of tests repeated much of the modelling with a modified set of Trust dummies. The initial set of dummies was based on the 11 Trusts. The second set increased this number to 14 by dividing Belfast into four districts. The effect was negligible for all but one of the models – i.e. it had no effect on the variable selection and changed the coefficients by no more than a few percent. The one exception is the "replacement" model for the weighted community variable. In this case, the significance of the variable KJSA reduces from 5% to 6%.

10.2 Unmet need tests and adjustments

To test for unmet need effects, the project has applied the methods recommended in the Deloitte and Touche paper "Inequalities in Health and Social Care Use: the Implications for Resource Allocation in the HPSS".

The paper describes two approaches. The first assumes that activity levels for a wide range of services will be strongly correlated with deprivation and that evidence of non-linearity in the relation between activity and deprivation, especially at high levels of deprivation, may be indicative of unmet need.

The second is concerned with variations in the relation between activity and deprivation within each of the supplying authorities. In resource allocation based on small area modelling it is customary to base final models on the average relation across all authorities. The Deloitte and Touche paper argues that it may be preferable to use an average of the relations in a sub-set of authorities whose activity varies most in relation to need.

We have only been asked to investigate the first of these – the shortfall approach. Applying this approach involves the following major steps

- Construct a best-fit and parsimonious model of the relation between service activity and needs drivers and any measure of supply.
- Use a spline regression to test for evidence of non-linearity in the relation between the Noble deprivation score and residuals from the model. Significant values of the coefficient of the spline variable may be a clue to unmet need.
- Regardless of the result of the spline test, force a suite of variables into the model. The recommended suite is a measure of limiting long-term illness, the Noble score, and several health variables that were synthetically estimated from the Northern Ireland Health and Social Well-being Survey.
- Discard any non-significant variables.
- Re-compute the model retaining the original variables and any of the unmet need test variables that are significant – paying particular attention to significant negative associations with deprivation scores.
- Use the revised coefficients of the original variables to compute the allocations.

The methodology and calculations are shown in Annex 3.

We attempted to add health variables and the Noble overall deprivation score into the models, following the Deloitte and Touche shortfall method for correcting for unmet need. None of the suggested variables was significant. In fact, we had already included the Noble score and limiting long-term illness in our standard dataset and only one of these, the LLTI, qualified as a variable in one of the models.

Similarly we have explored the possible significance of population density as an additional variable. This tended to behave as an inverse proxy for deprivation and was not significant.

In the spirit of the shortfall approach we looked for spline points in the relationship between activity and the variables in the preferred models and have included one example of such an analysis in a preliminary report. We do not reproduce the work in this final report, as there are no precedents for using splined variables to correct the values of coefficients. Before attempting such corrections significant extra work would need to be done. Firstly to establish the reason for the significance of the splined variable – this could be due to many possible reasons of which unmet need is only one. Secondly to check the statistical validity of making such a correction, especially in the context of a log-lin model.

10.3 Allocational implications

Two aspects of the modelling cause us some concern: the introduction of hospital and residential clients and the accuracy of the severity related cost weights. Data on the hospital and residential clients could not be entered directly into the model because of the lack of an originating ward code. Instead, the data on clients in the community had to be weighted-up (at Trust level) taking account, as far as possible, information on the age, sex and severity of those in hospital and residential care.

The cost weights were arrived at in a workshop where care professionals were asked to estimate the relative needs of clients of different ages and severity for most of the services available to those with learning disabilities. As in all such exercises, there are outstanding questions on the extent of consensus reached on the weightings and on the relevance of the weightings to the actual costs of care.

To test whether there should be serious cause for concern we have compared the allocational implications of models with and without the inclusion of the hospital and residential group and with and without the application of the cost weightings.

The results are shown in Table 44. The most striking feature is that these models are quite robust to changes in the dataset and weightings. The figures shown are the percentage of the total service allocation that would be received by each Trust as a result of applying both the age-sex weightings and the additional need model. In most cases any differences between the models result in changes of less than 0.5% of the national allocation. On this basis we conclude that this modelling is not very sensitive to the values of cost weights and that minor refinements to the weights would be unlikely to have significant impact on allocations. Nevertheless, it must be borne in mind that a small difference in the national percentage can represent a significant proportion of income, especially for a small Trust. High level allocational implications are included in this report to give an approximate comparison of the performance of different models and weighting systems, but we have left the more detailed and precise work in this area to the Department of Health, Social Services and Public Safety.

Table 44 Shares of overall PoC budget allocated to Trusts by recommended models (based on final dataset)

	Community only		Community, hosp and residential	
	Unweighted	Weighted	Unweighted	Weighted
(Model number)	1	2	3	4
S&E Belfast	9.0%	9.5%	8.7%	9.6%
N&W Belfast	11.7%	11.5%	12.3%	11.8%
Down&Lisburn	9.2%	9.5%	9.5%	9.1%
NDown&Ards	6.8%	6.8%	6.3%	6.8%
Causeway	5.6%	5.7%	5.4%	5.7%
Homefirst	17.9%	18.7%	17.3%	17.9%
Armagh&Dungannon	6.4%	6.4%	6.4%	6.4%
Newry&Mourne	6.1%	5.7%	6.3%	6.0%
Craigavon&Banbridge	7.4%	7.4%	7.4%	7.3%
Foyle	11.9%	10.7%	12.1%	11.0%
Sperrin Lakeland	8.1%	8.1%	8.3%	8.5%

This lack of sensitivity is confirmed by two later tests. The first of these – shown as model 3a in Tables 45 and 46 re-runs the modelling with a dataset based on extended weighting (including some weighting by Board) that takes the total number of clients in residential and hospital care to 1884 and 467 respectively – these data are not cost weighted.

The second supplementary test repeats the modelling for the original combined community hospital and residential data with, both weighted and unweighted for cost, but excludes the hospital cases.

Both tests have little impact on the coefficients in the original model and almost no effect on the allocations (see Table 46). It should be noted that the coefficients of the "recommended" models in Table 45 differ slightly from those in concluding Tables of the report and the Executive Summary. The calculations reported in Table 45 were conducted on a provisional dataset, but we are confident that the scale of difference between these models would be very similar if they were re-run with the final dataset.

Table 45 Supplementary models to test for effects of removing subsets of data and re-weighting (based on provisional dataset)

Model for unweighted dependent based on combined dataset			
	Rec model based on HRC SOSCARE data	Up-weighted to full totals in Prev study tables (incl. Board level weighting	Rec model but excl hosp data
Model	3	3a	3b
NOCARER	0.572	.580	.564
NOQUAL	0.551	.560	.560
KJAS	1.793	1.759	1.752
KDLA	2.805	2.780	2.801
CONSTANT	-0.527	-0.532	-0.526
R squared – dummies	16.9	16.5	16.3
R squared – full model	50.0	49.8	49.7
Model for weighted dependent based on combined dataset			

	Rec model based on HRC SOSCARE data	Rec model but excl hosp data	
Model	4	4a	
NOCARER	0.78	.767	
NOCENTH	0.912	.881	
NOQUAL	0.564	.572	
KJAS	1.43	1.485	
KDLA	2.53	2.416	
CONSTANT	-0.6576	-0.647	
R squared – dummies	12.7	11.8	
R squared – full model	41.8	41.8	

Table 46 Shares of overall PoC budget allocated to Trusts by supplementary models (based on provisional dataset)

Model 3 Community numbers weighted up by age and sex to include the hospital and residential clients (not weighted by cost)
Model 3a Community numbers weighted up by age and sex to include the residential (but not hospital) clients (not weighted by cost)
Model 3b Community numbers weighted up by age and sex to include the hospital and residential clients in the fullest version of the prevalence report (includes some Board level weighting) (not weighted by cost)

Model 4 Community numbers weighted up by age and sex to include the hospital and residential clients and further weighted by cost
Model 4a Community numbers weighted up by age and sex to include the residential (but not hospital) clients and further weighted by cost

	Unweighted			Weighted	
(Model number)	3	3a	3b	4	4a
S&E Belfast	9.2%	9.2%	9.2%	9.5%	9.5%
N&W Belfast	12.1%	12.1%*	12.2%*	12.0%	12.0%
Down&Lisburn	9.4%	9.4%	9.4%	9.1%	9.1%
NDown&Ards	6.7%	6.7%	6.7%	6.8%	6.8%
Causeway	5.5%	5.5%	5.5%	5.7%	5.7%
Homefirst	17.6%	17.6%	17.6%	17.9%	17.9%
Armagh&Dungannon	6.3%	6.3%	6.3%	6.4%	6.4%
Newry&Mourne	6.1%	6.1%	6.1%	6.0%	6.0%
Craigavon&Banbridge	7.3%	7.3%	7.3%	7.2%	7.2%
Foyle	11.5%	11.5%	11.5%	10.9%	10.9%
Sperrin Lakeland	8.2%	8.2%	8.2%	8.5%	8.5%

*value in 3b is 12.15% compared with 12.13% in 3a

10.4 Further redistributional issues

The Department of Health, Social Services and Public Safety have carried-out more detailed analyses of the allocational implications of the models – especially in relation to Western Board. We have followed-up this issue and give more details in Annex 4, where it is argued that it is not a conventional problem of unmet need, as the activity data from the Western Board Trusts suggest they respond to local differences in need in much the same way as Trusts elsewhere. Rather, it seems to be the case that other Trusts with similar socio-economic conditions and values of the relevant needs drivers seem to have identified more people with learning disabilities.

This additional work has reinforced our original conclusion that these are robust and well-specified models that are good predictors of the underlying activity data. Moreover, the previously reported conclusions on the lack of significance of any unmet need adjustments apply equally to these slightly modified models. The outstanding questions, which are outwith the modelling, are why is activity historically lower in the Western Board Trusts (once relevant socio-economic factors and age and sex are taken into account) and whether this should be addressed in the allocations. Again, it is worth noting that this is not a classic unmet need issue of the type discussed in the Deloitte and Touche paper, as these lower activity levels are specific to an administrative unit (i.e. may be related to supply) rather than to all wards with similar socio-economic characteristics regardless of the responsible Trust.

10.5 Confidence intervals

The variables in the modelling are standardised ratios of actual to expected client numbers (or cost weighted client numbers). In the ward level modelling the standard error of the ward level estimates is expressed as a log to base 10 of the ratio and is typically 0.13 for the unweighted models and 0.16-0.18 for the weighted models (see Table 47). When these figures are anti-logged (to base 10) the standard errors are respectively approximately 1.35 and 1.5. These will both have to be expressed as cost and client number ranges and converted to estimates for areas (such as Trusts) corresponding to groups of wards.

Table 47 Confidence intervals for the ward level modelling

Model	S.e of estimate	Anti-log of s.e.
Community		
Unweighted	0.134	1.36
Weighted	0.161	1.45
Combined		
Unweighted	0.131	1.35
Weighted	0.176	1.50

11. Conclusions and recommendations

We started this project with a suspicion that it might be difficult to model the need for services for learning disabilities because this need might be evenly distributed across the population.

Although a previous project had done much of the ground work in data collection and cleaning, the lack of detail on client record systems meant that it was not possible to obtain a ward code for the originating area of clients in residential and long-stay hospital care and these clients could not be entered directly into the analysis. Consequently various methods were adopted to weight-up the community care clients to take account of the numbers in these other two forms of care.

Moreover, the lack of information on the range of services used by individuals meant that an indirect approach had to be adopted to attach costs to clients. Cost weights were developed at a consensus building workshop and were computed in a way that enabled them to be applied to any client, regardless of the type of care actually received, provided we had details of the clients age and the severity of their learning disability.

These manipulations of the basic client data resulted in four different sets of models:

- for the numbers of clients in the community
- for clients in the community weighted by the cost of care for people in their age and severity group
- for clients in the community weighted up by age and sex (at Trust level) to take account of the clients in residential and hospital care.
- for clients in the community weighted up by age and sex and severity to take account of the clients in residential and hospital care.

We have been able to compute a recommended model for each of these datasets. Because the client rates differ markedly between age and sex groups, in all cases the activity variables (the dependents in the modelling) have been age-sex standardised.

All of these models have a log-lin form in which the dependent variable is logged (to base10) and the need drivers are unlogged. The variables and (unstandardised) coefficients in the models are as follows. They are estimated without the supply side factors though in all cases the available supply side variables were not significant.

Table 48 Recommended models

Variable name	Variable	Coefficient
Model for unweighted dependent based on clients in community R-squared (Trust dummies 16.8, full model 50.7)		
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.675
KJAS	proportion of children in job seekers allowance households	1.653
LLTI	proportion of adults with limiting long-term illness	0.180
CONSTANT		-0.484
Model for weighted dependent based on clients in community R-squared (Trust dummies 24.4, full model 50.8)		
NOCENTH	proportion of households with no central heating	0.820
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.959
KDLA	proportion of children in disability living allowance households	3.231
CONSTANT		-0.694
Model for unweighted dependent based on combined dataset R-squared (Trust dummies 17.1, full model 50.4)		
NOCARER	proportion of persons in no carer households (including at least one person with LLTI)	0.579
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.567
KJAS	proportion of children in job seekers allowance households	1.769
KDLA	proportion of children in disability living allowance households	2.781
CONSTANT		-0.521
Model for weighted dependent based on combined dataset R-squared (Trust dummies 12.5, full model 42.5)		
NOCARER	proportion of persons in no carer households (including at least one	0.745

	person with LLTI)	
NOCENTH	proportion of households with no central heating	0.914
NOQUAL	proportion of persons aged 16-64 with no qualifications	0.587
KJAS	proportion of children in job seekers allowance households	1.452
KDLA	proportion of children in disability living allowance households	2.671
CONSTANT		-0.649

Given the strong correlations between the various needs drivers, it is very likely that other combinations of variables could perform as well as the models we are suggesting. However when we have substituted alternative variables covering similar topics and forced in variables when the range of drivers appears to be limited, the suggested models proved surprisingly resilient to these tactics. In particular, the NOQUAL variable emerges strongly in almost all the modelling.

All but one of the models have respectable explanatory power (approximately 50%), the other has a value in excess of 40% and all are well specified. They have passed the sensitivity test of excluding one Board at a time and subdividing Belfast into four districts by increasing the number of dummy variables.

We have attempted to add health variables and the Noble overall deprivation score into the models, following the Deloitte and Touche shortfall method for correcting for unmet need. None of the suggested variables was significant. In fact, we had already included the Noble score and limiting long-term illness in our standard dataset and only one of these, the LLTI, qualified as a variable in one of the models.

Final choice of model

The four recommended models differ in two respects: whether they are based on the combined numbers of hospital, residential and community clients, rather than just those in the community and whether a service cost is attached to each client (based on their age and severity of LD).

In principle it seems desirable to use a model that is based on all clients and is cost weighted – provided that these costs are a valid proxy for need.

The two models which are exclusively based on the clients in community care are open to the obvious objection that they ignore services (and clients) that account for a large minority, or even majority, of the expenditure in this PoC. Moreover, they ignore the fact that the clients in residential care and hospitals have different age and, to a lesser extent, severity profiles than those in the community.

The case for the models based on the community dataset is that they distribute monies in ways that are very similar to those that try to include clients in residential and hospital care and they do not rely on the weighting assumptions that are involved in constructing a combined dataset.

Arguments can also be made both for and against using the age-severity cost weights developed in the consensus building workshop. On the one hand, they are our only means of taking some account of severity, given the lack of data on the services actually used by individual clients. On the other hand, it is easy to object to the method of construction of the weights, or dispute the recommended values.

In practice, as can be seen from Tables 44 and 46 the results from all these models are very similar when expressed as a percentage of the overall allocation they recommend for each Trust. The modelling does not appear to be sensitive to whether or not the combined or community dataset is used or whether client numbers or costs are modelled. The results of further tests, shown in Tables 45 and 46, endorse this point and show there is next to no measurable effect when the clients in hospital are excluded or when changes are made to the weighting to try to include clients from the prevalence study for whom there were no sub-Board details.

In many respects this lack of sensitivity is unsurprising. Owing to the limitations of the data on hospital and residential clients, these clients have had to be added at Trust level, and the Trust dummies will be bound to absorb some of the effect, especially in the modelling that is not cost weighted.

The similarity between the allocations from the cost weighted and unweighted models also shows very little sensitivity to the values of the weights. In effect, moving from no weights (i.e. all weights =1) to the weights from the workshop, only has an impact of more than 1% on the allocations for two Trusts and for no Trust exceeds 1.2%.

Given the similarity of the results and statistical properties of the four possible models, we feel there are no very strong grounds for choosing between them.

We do think there is a good prima facie case for using the combined (hospital, residential and community) dataset, however limited the method of weighting, because the residential and hospital clients tend to have different characteristics from those being cared for in the community.

The effect of adding these groups will only be fully realised if the age and severity related cost weights are also applied. This makes the case for the weighted combined model – though this has the lowest explanatory power.

In sum, if the weightings are a major concern then we would recommend the unweighted model based on the combined dataset, but on balance we just think the case for the combined weighted model is strongest – though this is a close call.

Glossary

Endogeneity (of supply side variables)

(Notes on endogeneity are adapted from Carr-Hill et al (Sept 1994) – Modelling NHS Inpatient Utilisation)

In developing a resource allocation formula, we wish to correct for variations in supply between areas. Effectively this means assuming that all supply in an area is at some national average appropriate to the level of needs found in that area.

Measures of supply ("supply variables") provide a means of testing this assumption. Supply can vary for many reasons in addition to those identified in the modelling as representing legitimate need. The analytic task is to find that part of the supply effect which is attributable to factors unrelated to the needs indicators in the model and to remove that part of the supply effect from the model.

The test of the assumption involves regressing the supply variables on the needs drivers, then including the residuals from these regressions alongside the needs drivers and supply variables as independents in a regression with the utilisation variable as dependent. The latter is sometimes known as the unrestricted question and its residual sum of squares is compared with that from a restricted equation – where the utilisation variable is simply regressed on the needs drivers and supply variables.

If the difference between the explanatory power of the two equations is significant then endogeneity has been demonstrated and two stage least squares methodology should be used.

The main features of this two stage process are firstly that the normal OLS procedure for identifying the best predictor variables is replaced by a process in which the supply variable is, in effect, replaced by its residual after it has been regressed on a set of candidate variables or "instruments". This process is used to search for the best predictor set of need drivers, which are then put into a simple OLS model (the second stage) in order to compute the coefficients for the allocation formula.

Forcing variables (into the model)

Multiple regression procedures in statistical packages use a variety of criteria to decide which variables should be included in an equation. The most commonly reported is the t value of the variable coefficient, but the tolerance (the extent of correlation with variables already in the equation) is usually considered when admitting or rejecting variables. Forcing a variable into an equation means suppressing these criteria and including a variable regardless.

FR22

A financial return from Trusts which gives details of provider expenditure by Programme of Care. Expenditure is split into three categories: Personal Social Services, Community, Hospital.

Functional form

The types of multivariate regression used in this modelling assumes that both dependent and independent variables have approximately normal distributions and that relations between these variables will be linear. Where one or both of these conditions are not met, it is customary to apply algebraic translations to the variables to either improve their approximation to normality, or to improve the linearity of the overall relationship.

Two descriptive statistics, the kurtosis and skewness of variables, will give an indication of the approximation to normality. High values of skewness indicate variables that have a long tail either side and kurtosis identifies variables that have distributions that are too flat or too steep.

Non-linearity is often indicated by low explanatory power, or poor specification. Translations that are used to improve approximations to normality and linearity include converting variables to an exponential, logarithmic or a square root form.

It may be appropriate to apply these translations to either or both the independent and dependent variables depending on the cause of the misspecification.

Specification (of a model)

Careful checks were made to ensure that the statistical models were well specified – i.e. that no systematic effects have been overlooked.
Specification errors can occur for various reasons:

- omission of a relevant explanatory variable
- inclusion of an irrelevant explanatory variable
- incorrect mathematical form of the regression equation
- incorrect specification of the covariance structure such that the error term is not normally distributed.

The test for misspecification employed here (the "Reset" test) involves testing the significance of the t value of the coefficient of the squared predicted values from the basic model when added to the model as an independent variable. In effect this is testing to see whether there are any systematic effects remaining in the residuals.

The Reset test should not be applied to 2SLS modelling. The preferred procedure involves computing an auxiliary equation derived from an OLS regression of the residuals from the 2SLS model against the full instrument and variable set in the 2SLS. The test statistic is the ratio of the sum of squares explained by this auxiliary equation to the estimated error variance for the 2SLS estimated utilisation equation. It should have a chi-squared distribution with degrees of freedom equal to the number of instruments in the auxiliary equation minus the number of repressors in the utilisation equality.

Standardisation

Where a phenomenon has been shown to be strongly related to basic demography, such as population age and sex, it will be inappropriate to make comparisons between populations without controlling for this relation.

In this project, the prevalence study found very difference rates of learning disability in different age and sex groups in the population. When we want to construct a ward level measure of the numbers of people with LD we then have to take account of the age-sex composition of the ward population. There are basically two ways in which this can be done.

Direct standardisation.

Here the LD rates are computed for each age-sex group fop each ward, then these rates are applied to the national average ward composition giving a corrected number of people with LD. The advantage of this approach is that the resulting metric can be numbers of people or services costs, rather than a dimensionless ratio; the disadvantage is that it tends to be unstable for small wards and for phenomena with very small numbers in some age-sex groups.

Indirect standardisation

The alternative (as used in this project) is to compute the national average RATES for each age sex group, then apply these to the ward population characterisistics, giving an expected value for each ward, assuming the national rates universally applied. A ratio can then be constructed of the expected to the actual numbers per ward. This method has he advantage of being far more robust than direct standardisation and tends to produce more powerful models. The problem is that national rates have to be used to convert the ratio back to costs or activity in order to use the resulting equations for resource allocation.

Spline regressions (dealing with partial non-linearity)

General departures from linearity are usually handled by transforming the dependent or independent variables. Departures from linearity over part of the range of an otherwise linear relation can be handled by spline coefficients. The following example describes the application of spline coefficients when we believe that there may be some non-linearity between prevalence of LD and the proportion over people without qualifications.

The base model includes the proportion of people without qualifications and any other significant variables that have been selected. To this we add a further independent variable that is zero in all but the 10% of wards with the highest values for the proportion of people with no qualifications. (this is the 90% spline point). In the top 10% of wards the variable is given the value of the proportion without education minus the proportion at the spline. If this new variable is significant we could interpret this as evidence of a change in slope at this point, which in certain circumstances might be interpreted as unmet need. In testing the models, we have re-run the regressions with spline points at the top 5%, 10%, 20% 40% 60% 80% values of the selected variables. Where the spline variable is significant and has an intuitively correct sign, it can be argued that the coefficients of the non-spline variables in the model should be those that were computed with the spline variables added, although the spline variables themselves should not be retained in the allocation formula.

Synthetic wards

As previously noted, a key requirement for the modelling is to choose areas that are sufficiently large to have robust values for the activity data and socio-economic indicators but not so large that they each contain a variety of conditions and thereby obscure any relations between activity and conditions.

Electoral wards are the obvious choice for this work as census and administrative statistics are available at this level, but rural wards may have populations that are too small to generate robust values for indicators of conditions and service activity. We considered using the next larger group of administrative units, District Electoral Areas, but tests with both census values and deprivation indicators have shown them to be socially heterogeneous and unlikely to produce conclusive models. Hence we felt we had no alternative but to construct a new set of "synthetic wards" In devising these wards, the aim was to produce areas with populations that are always greater than 2000 persons.

Trust dummies

Whenever activity data are used as dependent variables there is the risk that systematic supply influences may distort the modelling. Some of these phenomena are addressed with variables relating to the supply of specific services, but there may be more general or unmeasurable effects that we suspect are due to differences in policy and performance between agencies responsible for services. Although the current modelling is carried out at ward level, we suspect there may be influences due to the behaviours and policy of Trusts.

Therefore we include dummy variables that take values of one for each observation in the Trust to which they relate and values of zero for all other cases. Such a dummy variable is created for all but one of the Trusts (if all 11 Trusts have a dummy there are no degrees of freedom left in the modelling). It is customary to not use a dummy for the Trust with the largest number of cases.

ANNEX 1 Needs Drivers in Combined Set

POC7 and LD Modelling		Census source
Income		
Persons aged 18-64 in income support households	ADIS18_64	Claimant counts - for most of these indicators have proportion of persons in relevant benefit households as well as numbers of claimants
Persons aged 18-64 in income based JSA households	ADJSA	
Persons aged 18-64 in family credit households	ADWFTC	
Persons aged 18-64 in disability working allowance households	ADDLA	
Persons aged 18-64 in lone parent claimant households	ADLPP	
Persons aged 18-64 in JSA claimant households	ADJSA	
Unemployment (from census)		KS09
Other Economic		
Households where head is in a low SEG	LOWSEG	S344
Households where head is in a high SEG	HIGHSEG	S344
Households with no car	NOCAR	KS17
Households with 2 or more cars	TWOCAR	KS17
Households with 3 or more cars	THREECAR	KS17
Social environment/facilties		
Index of MD Social environment score	SOCENVSC	
Index of MD Access score	ACCSSC	
Household Structure		
Households with 3+ dependent children	HH3K	S007
Persons in single carer households	SNGCARER	S027
Persons in no carer households	NOCARER	S027
Persons aged 18-64 who are single, widowed or divorced	SWIDRCD	KS04
Single- never married	SINGLE	KS04
Married or living in relationship	MARRIED	KS04
Ex married	EXMAR	KS04
Household Tenure and facilities		
Persons aged 18-64 in social rented housing	SOCREN	KS18
Persons aged 18-64 in owner occupied housing	OWNOCC	KS18
Persons aged 18-64 in private rented housing	PRIVREN	KS18
Persons aged 18-64 in private rented housing assoc with employment	PRIVREM	KS18
Persons aged 18-64 in households without basic amenities	NOBASIC	KS19
Persons aged 18-64 in households without central heating	NOCENTH	KS19
Illness		
SMR under 65	U65SMR	
All age SMR	ALLSMR	
SMR under 75	U75SMR	
Persons with "not good health"	ADNGH	S016

Persons with "not good health" (standardised)	NGHS	
Persons aged 18-64 with a limiting long term illness	ADLLTI	S016
Persons aged 18-64 with a limiting long term illness (standardised)	LLTI	S016
Index of MD Health Score	HLTHSC	
Education		
Working age adults with no qualifications	NOQUAL	KS13
Index of MD Education Score	EDUCSC	
Ethnicity		
Persons in non-white ethnic groups	NONWHT	KS06
Multiple Deprivation		
All components and overall score for Noble indicator	OVSC	
Religion		
Persons of Catholic origin	CATHOL	KS07B
Persons of Protestant/Christian origin	PROTST	KS07B

Children and Family POC		**Census or other source**
Income		
Unemployed	ADUNEMP	KS09
JSA claimants	KJAS	
Noble child poverty score	CHILDPSC	
Other Economic		
Dependent children in households where head is in a low SEG	KLOWSEGA,B,,	S345
Dependent children in households where head is in a high SEG	KHGHSEGA,B	S345
Children in no car households	KNOCARA,B	S062
Children in households with 2 or more cars	KTWOCARA,B	S062
Household Structure		
Lone parents aged under 24	LONPU24	KS20.
Children in lone parent premium housholds	KLPP	
Households with 3+ dependent children	HH3K	S007
Children in overcrowded households	KOWCRAA,B	S357
Proportion of households with children 0-15 and lone parents of all ages	LPDEPK	S007
Households with dep (ALL) children	HHDEPK & HHALK	
Household Tenure and facilities		
Children in social rented housing	KSOCRENA,B	S359
Children in owner occupied housing	KOWNOCCA,B	S359
Children in private rented housing	KPRRENA,B	S359
Children in households without basic amenities	KNBASIC	S359
Children in households without central heating	KNOCENTH	S359
Illness		
SMR under 65	U65SMR	
Persons aged 18 and under with "not good health"	KNGH	S016

Persons aged 18 and under with a limiting long term illness	KLLTI	S016
Children in DLA claimant households	KDLA	
Education		
Working age adults with no qualifications	NOQUAL	KS13
Persons aged 16-18 not in full-time education		S028
Ethnicity		
Proportion in non-white ethnic groups	NONWHT	KS06
Religion		
Children of Catholic origin	KCATHO	KS07A
Children of Protestant/Christian origin	KPROT	KS07A
Claimants		
Children in JSA households	KJAS	Claimant count data
Children in WFTC households	KWTFC	Claimant count data
Children in Lone Parent Supplement HHolds	KLPP	Claimant count data
Children in income support households	KIS	Claimant count data
Multiple Deprivation		
All components and overall score for Noble indicator	OVSC	

Descriptive statistics for variables in needs driver set.

	Minimum	Maximum	Mean	Std. Deviation
ADLLTI	0.078	0.381	0.186	0.052
ADNGH	0.033	0.283	0.110	0.042
SNGCARER	0.011	0.085	0.036	0.010
NOCARER	0.117	0.493	0.281	0.062
OWNOCC	0.203	0.983	0.756	0.157
PRIVREN	0.007	0.628	0.069	0.052
SOCREN	0.000	0.774	0.168	0.151
PRIVREM	0.000	0.366	0.006	0.024
HIGHSEG	0.070	0.721	0.284	0.121
LOWSEG	0.028	0.568	0.242	0.102
NOCENTH	0.003	0.172	0.052	0.029
NOBASIC	0.000	0.038	0.008	0.006
NOQUAL	0.080	0.745	0.426	0.098
PROPNST	0.030	0.583	0.255	0.097
CATHOL	0.009	0.990	0.433	0.325
PROTST	0.007	0.969	0.538	0.311
NONWHT	0.000	0.056	0.008	0.007
SWIDRCD	0.297	0.901	0.479	0.090
NOCAR	0.033	0.748	0.240	0.147
TWOCAR	0.023	0.682	0.314	0.144
THREECAR	0.000	0.201	0.064	0.040
SINGLE	0.177	0.742	0.293	0.063
MARRIED	0.174	0.750	0.563	0.085
EXMAR	0.207	0.797	0.363	0.078
ADUNEMP	0.010	0.125	0.041	0.021
UPTO15S	249.000	2637.000	760.310	310.730
UPTO17S	293.000	3002.000	862.386	349.214
AD18TO64	1144.000	8080.000	1928.449	715.735
ALLAD	1359.000	8538.000	2354.591	834.504
ADOV65	122.000	1390.000	426.141	192.515
NHHOLD	571.000	3669.000	1196.696	459.679
KLOWSEGA	0.008	0.378	0.129	0.065
KLOWSEGB	0.009	0.428	0.148	0.072
KHGHSEGA	0.025	0.373	0.148	0.065
KHGHSEGB	0.033	0.428	0.171	0.075
KNOCARA	0.000	0.425	0.076	0.071
KNOCARB	0.000	0.485	0.094	0.085
KNOCARC	0.000	0.590	0.119	0.112
KTWOCARA	0.010	0.445	0.229	0.109
KTWOCARB	0.013	0.541	0.284	0.131
KTWOCARC	0.023	0.595	0.335	0.142
KOWCRAA	0.003	0.241	0.052	0.035
KOWCRAB	0.007	0.344	0.100	0.057
KPRVRENA	0.000	0.291	0.035	0.024
KPRVRENB	0.000	0.497	0.071	0.049
KSOCRENA	0.000	0.635	0.085	0.084
KSOCRENB	0.000	0.792	0.170	0.157

KOWNOCCA	0.063	0.610	0.388	0.113
KOWNOCCB	0.199	0.995	0.759	0.162
HH3K	0.035	0.307	0.131	0.048
LONPU24	0.000	0.089	0.019	0.016
LPDEPK	0.012	0.522	0.127	0.082
KNBASIC	0.000	0.018	0.003	0.003
KNOCENTH	0.000	0.077	0.018	0.013
KLLTI	0.011	0.124	0.053	0.019
KNGH	0.000	0.045	0.013	0.009
HHDEPK	0.094	0.699	0.374	0.080
HHALLK	0.131	0.802	0.508	0.093
KCATHOL	0.000	0.974	0.423	0.319
KPROT	0.000	0.863	0.413	0.263
POPDENS	0.107	113.828	14.675	18.905
KIS	0.011	0.814	0.216	0.160
KWFTC	0.028	0.433	0.236	0.072
KJAS	0.000	0.117	0.017	0.014
KLPP	0.001	0.607	0.063	0.080
ADLPP	0.000	0.090	0.011	0.013
ADJSA	0.003	0.130	0.033	0.023
ADIS	0.018	0.566	0.167	0.096
ADIS1864	0.007	0.534	0.134	0.092
ADIS65OV	0.045	0.828	0.328	0.147
ADDLA	0.016	0.312	0.102	0.049
ADWFTC	0.003	0.145	0.071	0.026
KDLA	0.004	0.079	0.031	0.012
ALLSMR	0.317	2.281	1.000	0.245
U75SMR	0.376	2.404	0.986	0.294
U65SMR	0.310	3.203	0.992	0.376
OVSC	1.132	76.046	20.747	14.626
INCSC	3.260	68.701	26.815	13.521
EMPSC	2.843	29.912	12.112	4.218
HLTHSC	-2.197	2.267	-0.038	0.741
EDUCSC	-2.589	2.475	-0.071	0.877
ACCSSC	-1.995	2.477	-0.012	0.787
SOCENVSC	-2.385	1.899	-0.044	0.744
HOUSSC	0.131	0.441	0.260	0.047
CHILDPSC	2.381	91.584	37.602	19.207
NWRDS	1.000	3.000	1.111	0.354
LLTI	0.470	1.822	1.000	0.237
NGHS	0.356	2.248	0.988	0.346

Annex 2

Method for weighting community dataset to take account of numbers in hospital and residential care

1. Main steps in the weighting by age and sex (used to prepare the dependent variable that is not to be weighted by cost)

- Identify the numbers of clients with missing data for age and /or sex in community, hospital and residential datasets.
- Remove these and weight –up each of the separate sets accordingly.
- In UCHT, where there are no details of client sex for large numbers, apply M or F randomly preserving the M/F ratio of the cases for which this information is present.
- Combine the hospital and residential datasets preserving age, sex and Trust codes.
- Combine these with the community dataset and compute the numbers in residential and hospital care as a proportion of the numbers in the same age and sex group (for each Trust) in community care.
- Weight-up the numbers in the community dataset by these proportions.

2. Main steps in the weighting by age sex and severity (used to prepare the dependent variable that is to be weighted by cost)
The method is analogous to that used above, but slightly more complex.

- Identify the numbers of clients with missing data for age or sex or severity in community, hospital and residential datasets.
- Remove these and weight –up each of the separate sets accordingly.
- In UCHT, where there are no details of client sex for large numbers, apply M or F randomly preserving the M/F ratio of the cases for which this information is present.

- As there is no information in severity for residential cases in UHCT and N&W Belfast these have to be given the national average severity rates for the respective age/sex groups.
- As there is no Trust level severity data for hospital clients in the available data sets, these have all been given national average severity ratings, by age.
- Combine the hospital and residential datasets preserving age, sex severity and Trust codes.
- Combine these with the community dataset and compute the numbers in residential and hospital care as a proportion of the numbers in the same age, sex and severity group (for each Trust) in community care.
- Weight-up the numbers in the community dataset by these proportions.

Annex 3 Unmet need tests and adjustments

To test for unmet need effects, the project has applied the methods recommended in the Deloitte and Touche paper "Inequalities in Health and Social Care Use: the Implications for Resource Allocation in the HPSS".

The paper describes two approaches. The first assumes that activity levels for a wide range of services will be strongly correlated with deprivation and that evidence of non-linearity in the relation between activity and deprivation, especially at high levels of deprivation, may be indicative of unmet need.

The second is concerned with variations in the relation between activity and deprivation within each of the supplying authorities. In resource allocation based on small area modelling it is customary to base final models on the average relation across all authorities. The Deloitte and Touche paper argues that it may be preferable to use an average of the relations in a sub-set of authorities whose activity varies most in relation to need.

We have only been asked to investigate the first of these – the shortfall approach. Applying this approach involves the following major steps

- Construct a best-fit and parsimonious model of the relation between service activity and needs drivers and any measure of supply.
- Use a spline regression to test for evidence of non-linearity in the relation between the Noble deprivation score and residuals from the model. Significant values of the coefficient of the spline variable may be a clue to unmet need.
- Regardless of the result of the spline test, force a suite of variables into the model. The recommended suite is a measure of limiting long-term illness, the Noble score, and several health variables that were synthetically estimated from the Northern Ireland Health and Social Well-being Survey.
- Discard any non-significant variables.
- Re-compute the model retaining the original variables and any of the unmet need test variables that are significant – paying particular attention to significant negative associations with deprivation scores.

- Use the revised coefficients of the original variables to compute the allocations.

Spline test using overall Noble index

The residuals from each of the recommended models were regressed against the deprivation index and spline versions of the index. The spline values tested were those that included wards with the top 5%, 10%, 20% 40% 60% 80% values of the index. The coefficients of the full version of the index in the regressions are shown in Table A.3.1. In all cases they are highly non-significant, which is unsurprising as the Noble overall score was not a preferred variable in the modelling. Equally unsurprising, significant values of the coefficients of the spline versions of the score were rare: occurring a very few cases in mid-range where they seemed to be caused by interactions with the full version of the variable.

It could be argued that we should have applied this test to the original activity data rather than the residual from the model. In which case we may have found spline effects and the Noble index would have been significantly correlated with activity.

Our argument for not following that approach is that the Noble score is not the best indicator of or proxy for deprivation when modelling learning disability. We will demonstrate that a spline effect can be found and corrected for in relation to the best predictor variable in the model (NOQUAL).

Table A.3.1 Coefficients of Noble overall deprivation score when used in conjunction with spline version of same variable to model the residuals from the four preferred models

	Beta	**T**	**Signif of T**
Community unweighted	.006	.127	.899
Community weighted	-.003	-0.079	.937
Combined unweighted	.0.020	-0.445	.656
Combined weighted	-0.022	-0.502	.616

Although these results suggest that we are unlikely to find unmet need effects in relation to the Noble measure of deprivation, we follow the recommended methodology and added the recommended suite of variables to each of the models. We estimate the models including supply variables (which are almost always insignificant), we add the four health variables using a stepwise procedure, retaining any that are significant, we then force the Noble score into the model.

An example of the results is shown in Table A.3.2. In all instances, none of the health variables, nor the Noble score is significant and there is no need for an adjustment. Though it should be noted that if we force the health variables into the model and retain them (even though they are not significant) in one case we can then get a significant and negative value for the Noble score. This looks as though the Noble score is trying to explain patterns of residuals created by retaining the nonsignificant health scores.

Table A.3.2 Results of adding health and Noble scores to models

	Combined dataset (unweighted)			**Combined dataset (weighted)**		
Variable	**Coeff**	**Beta**	**T**	**Coeff**	**Beta**	**T**
Model						
NOCARER	0.227	2.942	0.003	0.254	3.076	0.002
NOCENTH				0.110	2.615	0.009
NOQUAL	0.341	4.773	0.000	0.286	3.599	0.000
KJAS	0.141	3.444	0.001	0.093	2.119	0.035
KDLA	0.202	4.394	0.000	0.156	3.113	0.002
Noble						
OVSC	-0.095	-1.355	0.176	-0.098	-1.293	0.197
Health						
LLTI	0.094	0.996	0.320	-0.032	-0.304	0.762
GENHLTH	-0.032	-0.529	0.597	-0.003	-0.048	0.962
CIRCDIS	-0.047	-0.912	0.362	-0.061	-1.103	0.270
GENMH	-0.023	-0.441	0.660	-0.021	-0.387	0.699

Following the general principle of the shortfall approach, we have tested for non-linearity in the relation between the variables in the model (especially the best predictor NOQUAL) and the standardised dependents. There is some evidence of small spline effects – as in the example in Table A.3.3. Here there is a significant and negative relation with a spline version of NOQUAL (SP95NOQ: a variable that only has values for the wards with the top 95% of values on the full NOQUAL variable).

Including the spline variable changes the values of the coefficient in the model. The main effect is on the coefficient of NOQUAL, which increases from 0.675 to 0.739. We have tested the effect that such changes in the coefficients will have on allocations: in no cases change a Trust allocation by more than 0.1%. We have not taken these calculations any further because there are no precedents for using splined variables to correct the values of coefficients. Before attempting such corrections significant extra work would need to be done. Firstly to establish the reason for the significance of the splined variable – this could be due to many possible reasons of which unmet need is only one. Secondly to check the statistical validity of making such a correction, especially in the context of a log-lin model.

Table A.3.3 Effect of introducing spline version of NOQUAL to adjust for top-end non-linearity in model based on unweighted community data

Variable	Coeff	Beta	T	Signif T	Old coeff
NOQUAL	0.739	0.411	7.278	0.000	0.675
KJAS	1.602	0.113	2.867	0.004	1.653
LLTI	0.179	0.239	4.172	0.000	0.180
SP95NOQ	-1.026	-0.084	-2.260	0.024	--
Constant	-0.51				-0.51

Column headed "old coeff" shows the unstandardised coefficients in the original model without the spline variable.

Annex 4 Redistributional Issues

Concerns were expressed at the January CFRG meeting that the allocations produced by both models had major redistribution implications – especially in relation to Western Board. As there are a number of possible causes for such effects, it was agreed that further work would be done on this issue.

From tables in the report for the January meeting it can be seen that the redistributional effects are common to all four models – and to various supplementary models. As the methods of calculation and derivation of the standardised activity variables are different for each of the models, but the effect is common to all, a single computational error seemed unlikely.

The issue was first addressed by considering the residuals and predicted values from the models. This, coincidentally, identified a computational problem with the two models based on combined data from the community, hospital and residential sectors: that the nominator in the standardised activity calculations had not been corrected to take account of cases lacking valid ward codes. This was corrected and, as anticipated, made very little difference to the models as the correction factors were constant for each Trust and would be incorporated by the Trust dummies. The coefficients and allocational implications were virtually unchanged, the only major effect was a predictable reduction in the significance of the Trust dummies.

At the January CFRG it was suggested that the redistributional effect might be due to the model being insufficiently robust across Boards. That is, the values of the coefficients and relative significance of the variables would change markedly if the models were recomputed for single Boards or for the full dataset with particular Boards excluded. The original test for robustness, reported in the report for the January meeting, had addressed this issue and had not found such a problem. In fact, the model was both robust and well specified. In particular, the relation between activity and the most significant variable in the model (NOQUAL) was remarkably consistent across all Trusts.

We then further explored the residuals and predicted values from the model and identified the cause of the disparity.

If we examine the relation between the predicted values from the model including the Trust dummies and the actual levels of activity or cost, we get the figures shown in Table A.4.1

Table A.4.1 Values predicted from models including Trust dummies (also adjusted for age-sex effects)

	Actual clients as percent of NI total	Predicted nos. (model+ age-sex wts) (incl dummies)	Predicted costs (incl dummies)
Down&Lisburn	11.44%	11.38%	11.88%
N&W Belfast	10.23%	10.91%	12.24%
NDown&Ards	8.45%	7.90%	7.43%
S&E Belfast	9.88%	9.34%	11.47%
Causeway	6.60%	6.46%	5.73%
Homefirst	18.87%	18.67%	18.38%
Armagh&Dungannon	6.26%	6.13%	6.51%
Craigavon&Banbridge	6.77%	6.70%	6.62%
Newry&Mourne	6.26%	6.46%	6.10%
Foyle	8.51%	9.06%	7.67%
Sperrin Lakeland	6.72%	6.99%	5.97%

The similarity between the predicted and actual values for client numbers confirms the results of our other tests, that these models are robust good predictors.

Yet if we compare the above with the results produced by the model without the Trust dummies, as used for allocations, (Table A.4.2) we can see why there was cause for concern at the January meeting, especially in relation to the two Western Board Trusts where the predicted activity is several percent above the actual activity.

Table A.4.2 Values predicted from models excluding Trust dummies (also adjusted for age-sex effects)

	Model excl dummies (numbers)	Model excl dummies (costs)
Down&Lisburn	9.48%	9.12%
N&W Belfast	12.29%	11.76%
NDown&Ards	6.25%	6.76%
S&E Belfast	8.71%	9.58%
Causeway	5.39%	5.67%
Homefirst	17.33%	17.94%
Armagh&Dungannon	6.43%	6.36%
Craigavon&Banbridge	7.37%	7.29%
Newry&Mourne	6.34%	6.04%
Foyle	12.06%	10.98%
Sperrin Lakeland	8.34%	8.51%

The differences are explained by an inspection of the Trust dummies (Tables A.4.4-5)

Table A.4.3 Naming of Trust dummy variables in Tables A.4.4 and A.4.5

TRDUMA1	Armagh & Dungamnnon
TRDUMA2	Causeway
TRDUMA3	Craigavon and Banbridge
TRDUMA4	Down & Lisburn
TRDUMA5	Foyle
TRDUMA7	N&W Belfast
TRDUMA7A	N&W Belfast
TRDUMA8	N Down & Ards
TRDUMA9	Newry & Mourne
TRDUMA10	S&E Belfast
TRDUM10A	S&E Belfast
TRDUM10B	S&E Belfast
TRDUMA11	Sperrin Lakeland

Table A.4.4 Coefficients of model including Trust dummies predicting client numbers

Variable	Unstand Coefficients	Std	Standardized Coefficients	t -value	Signif.
	coeff	Error	Coeff		of coeff
(Constant)	-0.6488	0.0432		-15.0355	0.0000
TRDUMA1	0.0074	0.0368	0.0078	0.2023	0.8397
TRDUMA2	-0.0079	0.0369	-0.0082	-0.2151	0.8298
TRDUMA3	-0.0438	0.0344	-0.0495	-1.2701	0.2046
TRDUMA4	0.1038	0.0312	0.1386	3.3235	0.0010
TRDUMA5	-0.1648	0.0331	-0.2142	-4.9752	0.0000
TRDUMA7	-0.0174	0.0420	-0.0169	-0.4149	0.6784
TRDUMA7A	0.0145	0.0513	0.0116	0.2823	0.7778
TRDUMA8	0.0496	0.0325	0.0611	1.5251	0.1279
TRDUMA9	-0.0023	0.0404	-0.0023	-0.0577	0.9540
TRDUMA10	0.0758	0.0442	0.0634	1.7130	0.0873
TRDUM10A	0.0324	0.0474	0.0287	0.6841	0.4942
TRDUM10B	0.0262	0.0439	0.0225	0.5963	0.5512
TRDUMA11	-0.1666	0.0377	-0.1880	-4.4178	0.0000
NOCARER	0.7450	0.2797	0.2111	2.6639	0.0080
NOCENTH	0.9141	0.3519	0.1118	2.5975	0.0097
NOQUAL	0.5867	0.1679	0.2741	3.4951	0.0005
KJAS	1.4516	0.7452	0.0860	1.9478	0.0520
KDLA	2.6715	0.8945	0.1435	2.9866	0.0030

Table A.4.5 Coefficients of model including Trust dummies predicting cost weighted client numbers

Variable	Unstand Coefficients	Std	Standardized Coefficients	t -value	Signif.
	coeff	Error	Coeff		of coeff
(Constant)	-0.6488	0.0432		-15.0355	0.0000
TRDUMA1	0.0074	0.0368	0.0078	0.2023	0.8397
TRDUMA2	-0.0079	0.0369	-0.0082	-0.2151	0.8298
TRDUMA3	-0.0438	0.0344	-0.0495	-1.2701	0.2046
TRDUMA4	0.1038	0.0312	0.1386	3.3235	0.0010
TRDUMA5	-0.1648	0.0331	-0.2142	-4.9752	0.0000
TRDUMA7	-0.0174	0.0420	-0.0169	-0.4149	0.6784
TRDUMA7A	0.0145	0.0513	0.0116	0.2823	0.7778
TRDUMA8	0.0496	0.0325	0.0611	1.5251	0.1279
TRDUMA9	-0.0023	0.0404	-0.0023	-0.0577	0.9540
TRDUMA10	0.0758	0.0442	0.0634	1.7130	0.0873
TRDUM10A	0.0324	0.0474	0.0287	0.6841	0.4942
TRDUM10B	0.0262	0.0439	0.0225	0.5963	0.5512
TRDUMA11	-0.1666	0.0377	-0.1880	-4.4178	0.0000

NOCARER	0.7450	0.2797	0.2111	2.6639	0.0080
NOCENTH	0.9141	0.3519	0.1118	2.5975	0.0097
NOQUAL	0.5867	0.1679	0.2741	3.4951	0.0005
KJAS	1.4516	0.7452	0.0860	1.9478	0.0520
KDLA	2.6715	0.8945	0.1435	2.9866	0.0030

The names assigned to the Trust dummies are shown in Table A.4.3. Looking at all three of the above tables you will see that, by convention, the group with the largest number of observations is not assigned a dummy but becomes the baseline for the dataset. Here, Homefirst is used in this way. The values of the coefficients for the Trust dummies in the modelling can then be interpreted as a measure of the extent to which the average activity levels in each Trust differ from those in Homefirst, after controlling for the local values of the predictor variables. For example, in Table A.4.4. part of South and East Belfast (dummy 10) has the highest positive value amongst the dummies and Foyle and Sperrin Lakeland have the largest negative values. This can be interpreted as suggesting that activity in part of S&E Belfast is greater than expected and less than expected in the two Western Board Trusts.

The values predicted by the model including the Trust dummies (as in Tables A.4.4 and A.4.5) incorporate the Trust level effects, so the prediction for each ward in each Trust will be effected by the value of the relevant Trust dummy. The relation is not simple in this case because the activity variable has been both standardised and logged, but, basically, the greater the negative value of a Trust dummy, the greater the reduction in the predicted values. As can be seen from Tables A.4.4 and A.4.5, the largest negative values are for the Western Board Trusts.

When the model is run without the Trust dummies – as would be done for resource allocation to remove Trust level historical and other effects – the predictions for the Western Trusts are not reduced by the dummies and their allocations are based on the cost and activity levels that would be expected in these Trusts from the overall pattern of Northern Ireland response to need for LD services.

This is not a conventional problem of unmet need, as the activty data from the Western Board Trusts suggest they respond to local differences in need in much the same way as Trusts elsewhere. Rather, it seems to be the case that other Trusts with similar socio-economic conditions and values of the relevant needs drivers seem to have identified more people with learning disabilities.